Europass Curriculum Vitae

Personal information

First name(s) / Surname(s)	**Victor-Emil Neagoe**
Address(es)	Str. Baia de Arieş nr. 3, bl. 5B, scara C, apart. 105, sector 6, Bucureşti, Romania, code 060801
Telephone(s)	Personal: +40 214114700 Mobile: +40 721235020
Fax(es)	+40 214114700
E-mail	victoremil@gmail.com
Nationality	Romanian
Date of birth	31.05.1947
Gender	Male

Desired employment / Occupational field	**Professor, Faculty of Electronics, Telecommunications and Information Technology, POLITEHNICA University of Bucharest (Long Term Expert).**

Work experience

Period	May 1991 – currently
Occupation or position held	Authorized Ph.D. supervisor
Main activities and responsibilities	Supervisor of Ph.D. students/theses

Name and address of employer	POLITEHNICA University of Bucharest, Splaiul Independenţei nr. 313, Bucharest ,060042 Romania
Type of business or sector	Higher technical education
Period	October 1, 1991-currently
Occupation or position held	Professor, Faculty of Electronics, Telecommunications and Information Technology
Main activities and responsibilities	- Teaching Courses: *Pattern Recognition and Artificial Intelligence; Data Mining; Computational Intelligence; Digital Signal Processing; Decision, Estimation and Information Processing* - Research (Director of several research projects: *Multiple System for Biometric Identification, Face&Iris Recognition, Neural Self-Organizing Models for Pattern Recognition, Neural Expert System for Pattern Recognition in Satellite Imagery, Neural Networks for Vehicular Robotics, Image Data Compression*).
Name and address of employer	POLITEHNICA University of Bucharest, Splaiul Independenţei nr. 313, Bucharest , 060042 Romania
Type of business or sector	Higher technical education
Period	January 1995-July 1995
Occupation or position held	Invited Professor
Main activities and responsibilities	Teaching/Plenary Lectures/Research
Name and address of employer	University of Gent, Belgium, St. Pietersnieuwstraat 33, 9000 Gent, Belgium
Type of business or sector	Higher technical education
Period	September 1, 1970- October 1, 1991
Occupation or position held	Assistant Professor/Lecturer
Main activities and responsibilities	-Teaching Lectures, Seminars, Laboratories: *Information Transmission Theory,Television, Applied Electronics*; supervisor of final diploma projects -Research: projects in the field of *image data compression* and *pattern recognition*
Name and address of employer	POLITEHNICA University of Bucharest, Splaiul Independenţei nr. 313, Bucharest , 060042 Romania
Type of business or sector	Higher technical education

Education and training

Dates	September 1980 – September 1981
Title of qualification awarded	Master / Postuniv UNESCO in Applied Mathematics and Informatics (average of marks 10)
Principal subjects/occupational skills covered	- Mathematical Models - Probabilities and Statistics - Dynamic Programming - Informatics - Management
Name and type of organisation providing education and training	Bucharest University of Bucharest, Faculty of Mathematics/UNESCO
Dates	October 1973 – October 1976
Title of qualification awarded	PhD degree in Electronics (supervisor Prof. G. Cartianu), 1976
Principal subjects/occupational skills covered	- Signal and System Theory - Information Transmission Theory - Image Data Compression
Name and type of organisation providing education and training	POLITEHNICA Institute of Bucharest, Faculty of Electronics and Telecommunications
Dates	October 1965 – July 1970
Title of qualification awarded	Electronics Engineer (head of series, with Honor Diploma, average of marks 9.97 out of 10)
Principal subjects/occupational skills covered	- Mathematics - Signal and Systems Theory - Information Transmission Theory - Electronic Circuits - Computer Programming
Name and type of organisation providing education and training	POLITEHNICA Institute of Bucharest, Faculty of Electronics and Telecommunications

Level in national or international classification

Personal skills and competences

Mother tongue(s) **Romanian**

Other language(s)

Self-assessment	Understanding				Speaking				Writing	
European level (*)	Listening		Reading		Spoken interaction		Spoken production			
English	C2	Proficient user	C2	Proficient user	C1	Proficient user	C1	Proficient user	C2	Proficient u
French	C2	Proficient user	C2	Proficient user	B1	Independent user	B1	Independent user	A2	Basic use

(*) Common European Framework of Reference for Languages

Social skills and competences

Experience for PhD student teaching and supervising, as well as for leading the student research teams and their final projects. He has also experience in leading and participating as partner in research projects.

Organisational skills and competences

Experience in project and team management.

Technical skills and competences

- Experience of 47 years in university teaching and research
- PhD supervisor since 1990
- Competence fields for university teaching: pattern recognition, computational intelligence (artificial neural networks; fuzzy systems, genetic algorithms, swarm intelligence, artificial immune systems, ant colony optimization), data mining, digital signal processing, computer vision, detectior estimation and information processing.
- Competence fields for research: computational intelligence, pattern recognition, data minin remote sensing image analysis, change detection, biometrics, computer vision, image compression
- Author of more than 150 published papers.

Computer skills and competences

Microsoft Office (Word, PowerPoint etc.), Matlab.

Artistic skills and competences

Poetry, author of a booklet of poetry called *"Notre espace vectoriel- Poemes pour le tiroir"* written in 1989 and published in 1992 in France.

Other skills and competences

- Member IEEE (Institute of Electrical and Electronics Eng., New York) since 1978
- Senior Member IEEE since 1984.
- Who's Who in the World: 1998 (15^{th} Edition); 2011 (28^{th} Edition), 2012 (29^{th} Edition), 201 (30^{th} Edition), 2014 (31^{th} Edition), 2015 (32^{th} Edition), 2016 (33^{rd} Edition)
- Who's Who in Science and Engineering:2005-2006; 2011-2012; 2016-2017

Additional information

References may be given at request

Appendices

List of published papers

Date: January 15, 2018

Victor-Emil Neagoe

LISTA DE LUCRARI PUBLICATE
Prof.dr.ing. Victor-Emil Neagoe

A. TEZA DE DOCTORAT

***V. E. Neagoe**, Sinteza in domeniul timp a unor sisteme optimale cu esantionare diferentiala pentru transmisiuni in cod de impulsuri,* Institutul Politehnic Bucuresti, 1976.(conducator stiintific: acad. prof. Gheorghe Cartianu) Domeniul tezei: (a) *domeniul ca tematica*: prelucrarea semnalelor; prelucrarea imaginilor; teoria transmisiunii informatiei. (b) *domeniul ca terminologie oficiala*: electronica si telecomunicatii

B. ARTICOLE şi COMUNICARI

Ba. Articole publicate în reviste de specialitate

V. E. Neagoe, S.V. Carata, „Subject Independent Drunkenness Detection Using Pulse-Coupled Neural Network Segmentation of Thermal Infrared Facial Imagery”, *International Journal of Mathematical and Computational Methods,* Vol. 1, 2016, pp. 305-312.

V. E. Neagoe, V. Chirila-Berbentea, “A New Approach to Unsupervised Classification of Hyperspectral Earth Observation Imagery Using a Gaussian Mixture Model, *International Journal of Signal Processing,* Vol. 1, 2016, pp. 134-137.

V. E. Neagoe, R. M. Stoica, A. I. Ciurea, L. Bruzzone, and F. Bovolo, “Concurrent Self-Organizing Maps for supervised/unsupervised change detection in remote sensing images,” *IEEE J. Selected Topics Appl. Earth Obs. Remote Sens.,* vol. 7, no. 8, pp. 3525–3533, Aug. 2014. (Factor impact=2.827).

E. C. Neghină, **V. E. Neagoe,** R. M. Stoica and A. D. Ciotec, “Neural and Ant Colony Optimization versus Statistical Models for Supervised Classification of Multispectral Remote-Sensing Imagery”, *Scientific Bulletin of the Polytechnic University of Bucharest*, Series C, Vol. 75, Iss. 3, 2013, pp. 87-100, ISSN 2286-3540.

A. D. Ciotec, **V. E. Neagoe**, A. P. Bărar, “Concurrent Self-Organizing Maps for Pedestrian Detection in Thermal Imagery”, *Scientific Bulletin of the Polytechnic University of Bucharest*, Series C, Vol. 75, Iss. 4, 2013, ISSN 2286-3540.

V. E. Neagoe, M. Neghina, M. Datcu, "Neural Network Techniques for Automated Land-Cover Change Detection in Multispectral Satellite Time Series Imagery", *International Journal of Mathematical Models and Methods in Applied Sciences,* Issue 1, Volume 6, 2012, pp. 130-139, ISSN: 19980140, NAUN Press.

V.E. Neagoe, C.T. Tudoran, “A Neural Machine Vision Model for Road Detection in Autonomous Navigation”, *University Politehnica of Bucharest, Scientific Bulletin Series C* - Electrical Engineering, No 2, 2011, pp. 167-178.

V. Neagoe and A. Ropot, "Concurrent Self-Organizing Maps - A Powerful Artificial Neural Tool for Biometric Technology", in *Harbour Protection Through Data Fusion Technologies*, NATO Science for Peace and Security Series-C: Environmental Security, pp. 291-298, Springer, 2009.

V. Neagoe and A. Ropot, " A New Neural Approach for Pattern Recognition in Space Imagery", in *Harbour Protection Through Data Fusion Technologies*, NATO Science for Peace and Security Series-C: Environmental Security, pp. 283-289, Springer, 2009.

V. E. Neagoe, “An optimum color feature space and its applications for pattern recognition”, *WSEAS Transactions on Signal Processing*, issue 12, vol. 2, pp. 1537-1543, December 2006, ISSN: 1790-5022.

V. Neagoe, “A Syntactical Self-Organizing Map with Levensthein Metrics and Its Application for Autmatic Translation”, *Scientific Bulletin of the „Politehnica” University of Timisoara*, Tom 49 (63), fascicola 1, 348-351 (2004), ISSN 1583-3380

V. Neagoe, A. D. Ropot, “Neural versus statistical approaches for pattern recognition in space imagery“, *Scientific Bulletin of the „Politehnica” University of Timisoara*, Tom 49 (63), fascicola 1, 343-347 (2004), ISSN 1583-3380.

V. Neagoe, ”A Neural Approach to Compression of Hyperspectral Remote Sensing Imagery”. In: Reusch, B. (ed.): *Computational Intelligence. Theory and Applications (International Conference, 7th Fuzzy Days Dortmund*, Germany, October 1-3, 2001 Proc.). ISBN: 3-540-42732-5. Springer, Berlin (2001). pp. 436-449.

V. Neagoe and F. Szabo**,** “A Neural Compression of Color Image Sequences”, *Buletinul Ştiinţific al Universităţii “Politehnica” Timişoara (Scientific Bulletin of the Polytechnic University of Timişoara, Romania)*, Tom 45 (59), Fascicula 1 (2000), vol. I, 269-272.

V. Neagoe and I. Fratila, “A Neural Classification of Multispectral Satellite Imagery using the Fuzzy ARTMAP Model”, *Buletinul Ştiinţific al Universităţii “Politehnica” Timişoara (Scientific Bulletin of the Polytechnic University of Timişoara, Romania)*, Tom 41 (55), Fascicula 1 (2000), vol. I, 273-278.

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V. Neagoe and B. Georgescu**,** "A neural vector quantization for image sequence compression", *Real World Applications of Intelligent Technologies* (eds. B. Reusch and D. Dascalu), printed by National Institute for Research and Development in Microtechnology, Bucharest, 1998, pp. 86-90. 3

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V. Neagoe, C. Popescu, M. C. Vanwormhoudt, I. Lemahieu, and W. Philips, "Satellite image classification using feature extraction of a line pattern structure cascaded with a neural network", *Buletinul Ştiinţific al Universităţii "Politehnica" Timişoara (Scientific Bulletin of the Polytechnic University of Timisoara, Romania)*, Tom 41 (55), Fascicula 1 (1996), vol. II, 219-224.

V. Neagoe, I. Frăţilă, and F. Szabo, "Inteligent image compression using a Hebbian network cascaded by a circular self-organizing map", *Buletinul Ştiinţific al Universităţii "Politehnica" Timişoara (Scientific Bulletin of the Polytechnic University of Timişoara, Romania)*, Tom 41 (55), Fascicula 1 (1996), vol. I, 33-38.

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V. Neagoe, "Transmisiune M-ary optimală în cod de impulsuri de formă polinomială", *Probleme de Automatizare, vol. X*, Ed. Academiei RSR, Bucureşti, 1978, pp. 207-219.
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V. Neagoe, R. Hahn, B. Lucaschi, "Proiectarea cu ajutorul calculatorului numeric a amplificatoarelor de bandă largă tranzistorizate cu corecţie la frecvenţe înalte pentru obţinerea unei caracteristici de frecventă de tip MLA", *Telecomunicaţii*, decembrie 1973.
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V. Neagoe, "Contribuţii la calculul circuitelor de corecţie la frecvenţe înalte ale amplificatoarelor de videofrecventa tranzistorizate", *Telecomunicaţii*, iunie 1972.

Bb. Lucrari publicate în volumele unor manifestări stiintifice internaţionale

2017
V.E. Neagoe, V. Chirilă-Berbentea, "A novel approach for semi-supervised classification of remote sensing images using a clustering-based selection of training data according to their GMM responsibilities*," Proceedings of 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* Fort Worth, Texas, USA, July 23–28, 2017, pp. 4730-4733.
V.E. Neagoe, C. E. Neghina, V. Chirila-Berbentea, **"**A genetic algorithm approach to purify the classifier training labels for the analysis of remote sensing imagery," *Proceedings of 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* Fort Worth, Texas, USA, July 23–28, 2017, pp. 3234-3237.
V. E. Neagoe, S.V. Carata, "Drunkenness diagnosis using a neural network-based approach for analysis of facial images in the thermal infrared spectrum,"*Proceedings of 2017 E-Health and Bioengineering Conference (EHB),"* Sinaia, Romania, June 22-24, 2017, pp. 165-168.

2016

V.E. Neagoe, A. D. Ciotec, S.V. Carata**,** „A new multispectral pixel change detection approach using pulse-coupled neural networks for change vector analysis, " *Proc. 2016 IEEE International Geoscience and Remote Sensing Conference (IGARSS 2016)*, Beijing, China, July 10-15, 2016, pp. 3386-3389, ISBN:978-1-5090-3332-4, ISSN: 2153-6996.

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V. E. Neagoe and C. E. Neghina, "Feature Selection with Ant Colony Optimization and its Applications for Pattern Recognition in Space Imagery", *Proc. 11th International Conference on Communications (COMM 2016),* Bucharest, Romania, June 9-11, 2016, pp. 101 – 104, ISBN:978-1-4673-8197-0.

S.V. Carata, **V.E. Neagoe**, "Pulse-Coupled Neural Network approach for image segmentation and its pattern recognition application," *Proc. 11th International Conference on Communications (COMM 2016),* Bucharest, Romania, June 9-11, 2016, pp. 61-64, ISBN:978-1-4673-8197-0.

V.E. Neagoe, S.V. Carata, A. D. Ciotec „An Advanced Neural Network-Based Approach for Military Ground Vehicle Recognition in SAR Aerial Imagery*", Proc. 18-th International Conference on "Scientific Research and Education in the Air Force"(AFASES),* Brasov, Romania, , May 26-28, 2016. pp.41-47.

2015

V. E. Neagoe, C. E. Neghina , " Training label cleaning with ant colony optimization for classification of remote sensing imagery," *2015 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2015)*, Milano, Italy, July 26-31, 2015, IEEE Catalog Number: CFP15IGA-USB, ISBN: 978-1-4799-7928-8, pp. 421-424 (ISI, IEEE Xplore)

V. E. Neagoe, S. V. Carata, A. D. Ciotec, "Automatic target recognition in SAR imagery using Pulse-Coupled Neural Network segmentation cascaded with virtual training data generation CSOM-based classifier," *2015 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2015)*, Milano, Italy, July 26-31, 2015, IEEE Catalog Number: CFP15IGA-USB, ISBN: 978-1-4799-7928-8,pp.3274-3277 (ISI, IEEE Xplore).

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2014

V. E. Neagoe, R. M. Stoica, "A new neural network-based approach for automatic annotation of remote sensing imagery," *2014 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2014)*, Quebec City Q.C., Canada, July 2014, pp. 1781 – 1784.

V. E. Neagoe, A. Ciurea, L. Bruzzone, F. Bovolo, "A novel neural approach for unsupervised change detection using SOM clustering for pseudo-training set selection followed by CSOM classifier", *2014 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2014)*, Quebec City Q.C., Canada, July 2014, pp. 1437 – 1440.

V. E. Neagoe, A. I. Ciurea, R. M. Stoica, . Bovolo and L. Bruzzone, "Unsupervised Change Detection with Concurrent Self-Organizing Maps," *Proc. of ESA-EUSC-JRC 9th Conference on Image Information Mining (the Sentinels Era)*, 5-7 March 2014, Bucharest, Romania, Publications Office of the European Union, Luxembourg, pp. 21-24, ISBN 978-92-79-36160-9.

V. E. Neagoe, C.E. Neghina, L. Bruzzone, F. Bovolo, "Ant colony optimization band selection for classification of multispectral Earth observation imagery," *Proc. on Big Data from Space Conference (BIDS'14)*, 12-14 Nov. 2014, Frascati, Italy, Publications Office of the European Union, Luxembourg, 2014, pp. 291-294,ISBN 978-92-79-43252-1.

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2013

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E. BREVETE DE INVENTII

1. V. Neagoe, “Metodă şi sistem de traducere automată cu corecţie a erorilor de tastare utilizând o reţea neuronală sintactică cu autoorganizare”, Brevet de invenţie, nr. 116684B1/30.03.2001, OSIM, Romania.
2. V. Neagoe, “Dispozitiv diferential neliniar pentru conversia digitala cu compresie de spectru a semnalelor de televiziune”, Brevet de inventie nr. 73603/1978, OSIM, Romania.
3. V. Neagoe, “Metoda sisistem de transmisiune multipla prin modulatie “n+1”-dimensionala in cod de impulsuri de forma polinomiala”, Brevet de inventie nr. 70645/1978, OSIM, Romania.
4. V. Neagoe, “Metoda si dispozitiv de codare optimala a semnalelor video prin modulatie delta adaptiva cu sistem de dubla predictie”, Brevet de inventie nr. 70594/1977, OSIM, Romania.
5. V. Neagoe, “Metoda si dispozitiv de transmisiune M-ary prin modulatie log2(n+1)-dimensionala in cod de impulsuri de forma polinomiala”, Brevet de inventie nr. 69568/1977, OSIM, Romania.
6. A. Spataru, **V. Neagoe,** “Modulator delta adaptiv pentru codarea semnalelor video”, Brevet de inventie nr. 63977/1976, OSIM, Romania.

F. CONTRACTE (SELECTIE)

Fa. Contracte la care candidatul a fost responsabil

V. Neagoe (director proiect), *Sistem multiplu de identificare biometrica pentru prevenirea terorismului – SIB*, (Program CEEX), contract 17-06-17/UPB, Beneficiar direct : Optoelectronica 2001 SA; Beneficiar final: Agentia Spatiala Romana, (2006-2009).
V. Neagoe (director grant), *Infrastructura modulara pentru sistem de acces utilizand parametri biometrici – FACE&IRIS RECOGNITION – FAIR* (Programul National Securitate), nr. 17-06-01/UPB, Beneficiar: Agentia Spatiala Romana, (2005-2006).
V. Neagoe (director grant), *Module neuronale autoorganizabile pentru recunoasterea formelor (*Grant cu Academia Romana, nr. 171/2003 – Acad. Romana, nr. 17-03-06/UPB), (2003-2004).
V. Neagoe (director grant), *Sistem neural expert pentru recunoasterea formelor in imageria satelitara* (Contract de cercetare cu Agentia Nationala pentru Stiinta, Tehnologie si Inovare (ANSTI), nr. Contract Adit. 351/1999/II – ANSTI (MCT), nr. 17-96-04/UPB); Beneficiar: Agentia Spatiala Romana, (1996-1999).
V. Neagoe (director grant), *Compresia secventelor de imagini* (Contract de cercetare cu Agentia Nationala pentru Stiinta, Tehnologie si Inovare (ANSTI), tema A23/1999 inclusa in contractul nr. 836/96 – ANSTI (MCT)); Beneficiar: Agentia Spatiala Romana, (1997-1999).
V. Neagoe (director grant), *Retele neurale pentru compresia si segmentarea imaginilor color* (Contract cu Ministerul Educatiei Nationale),(1997-1998).
V. Neagoe (director grant), *Retele neurale pentru robotica vehiculara (*Contract cu Ministerul Cercetarii si Tehnologiei), (1996-1998).
V. Neagoe (director grant), *Recunoasterea formelor cu aplicatii in imageria satelitara* (Beneficiar: Agentia Spatiala Romana), (1994-1996).
V. Neagoe (director grant), *Compresia de date pentru imageria satelitara* (Beneficiar: Agentia Spatiala Romana), (1993-1994).

15.01.2018. Victor-Emil Neagoe

Prof. **Victor Neagoe**-

lista cu cele mai semnificative 5 lucrari publicate

1**. V. E. Neagoe**, "*Predictive Ordering and Linear Approximation for Image Data Compression*", **IEEE Transactions on Communications, (Q1),** vol. **36,** issue 10, October, 1988, pp. 1179-1182, **DOI: 10.1109/26.7539**, **WOS:A1988Q056500015**.

2. **V. E. Neagoe**, *"Chebyshev nonuniform sampling cascaded by Discrete Cosine Transform for optimum interpolation",* **IEEE Transactions on Signal, Acoustics and Speech Processing** (in prezent **IEEE Transactions on Signal Processing**),(**Q1**), vol. 38, issue 10, October 1990, pp. 1812-1816, **DOI**: **10.1109/29.60116**, **WOS**:**A1990EA28000021.**

3. **V. E. Neagoe**, *"A 2-dimensional nonuniform sampling expansion model"***, Signal Processing, (Q1),** Elsevier, vol. **33,** issue 1, July 1993, pp. 1-21, **DOI: 10.1016/0165-1684(93)90074-K, WOS:A1993MD67200001.**

4. **V. E. Neagoe**, *"Inversion of the Van der Monde Matrix",* **IEEE Signal Processing Letters**, **(Q2)**, vol. **3**, (1996), pp. 119-120, **DOI: 10.1109/97.489066**,**WOS:A1996UF76300008.**

5. **V. E. Neagoe**, R. M. Stoica, A. I. Ciurea, L. Bruzzone, F. Bovolo, "*Concurrent Self-Organizing Maps for supervised/unsupervised change detection in remote sensing images",* **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,(Q2),** vol. 7, no. 8, pp. 3525–3533, Aug. 2014, **DOI: 10.1109/JSTARS.2014.2330808** , **WOS:000343055200031.**

Fişa de calcul şi de sustinere a îndeplinirii standardelor minimale specifice domeniului (FiȘA GLOBALĂ)

Prof. NEAGOE Victor-Emil

Departamentul Electronica Aplicata si Ingineria Informatiei
Facultatea de Electronica, Telecomunicatii si Tehnologia Informatiei
Comisia Electronica, Telecomunicatii si Nanotehnologie (Anexa nr. 11)

30 septembrie 2020

CENTRALIZATOR

Condiţii minimale pentru profesor la Comisia de Electronica, Telecomunicatii si Nanotehnologie (Anexa nr. 11)	Val. Min.	Obţinut
A1 Activitate didactică / profesională	100	112.500
A2 Activitatea de cercetare	600	2318.727
A3 Recunoașterea impactului activității	150	813.600
INDICATORUL DE MERIT (A = A1 + A2 + A3))	850	**3244.827**
A1.1.1-A1.1.2 Cărți de specialitate	1	4
A2.1 Articole în reviste cotate ISI și în volumele unor manifestări științifice indexate ISI proceedings	15	54
din care în reviste cotate ISI Q1 sau Q2 [10]	3	7
A2.4.1 Granturi/proiecte câștigate prin competiție (Director / Responsabil partener)	2	9
A3.1.1 Numar de citări în cărți, reviste cotate ISI și în volume ale unor manifestări ştiinţifice ISI (WOS) [11]	25	102
Factor de impact ISI cumulat pentru publicatii [12]	10	40.825

PREZENTARE DETALIATA

Nr.crt.	A1 - Activitate didactică și profesională				Punctaj
	A1.1.1 Cărţi de autor sau capitole [1] de specialitate în edituri cu ISBN (Cărţi / monografii) - internaționale	Tip [1]	Nr. Autori	>50 biblioteci străine conform WorldCat [2]	
	… Includeţi ISBN:				0.000
	A1.1.2 Cărţi de autor sau capitole de specialitate în edituri cu ISBN (Cărţi / monografii) - naționale	Tip [1]		Nr. Autori	
1	**V. Neagoe**, O. Stănăşilă, Teoria recunoaşterii formelor, Editura Academiei Române, Bucureşti, 1992, ISBN: 973-27-0341-5, 400p (cod CNCSIS: 164).	Carte	2		25.000
2	**V. Neagoe**, O. Stănăşilă, Recunoaşterea formelor şi reţele neurale : Algoritmi fundamentali, Editura Matrix Rom, Bucureşti, 1999, ISBN: 973-939-035-8, 288p (cod CNCSIS: 39).	Carte	2		25.000
3	**V. Neagoe**, Inteligenţa computaţională, capitol (32p) al cărţii Enciclopedia Matematică, pp. 1056-1087 (coordonatorii volumului Marius Iosifescu si O. Stănăşilă), Ed. AGIR, Bucuresti, 2010, ISBN: 978-973-720-288-8, 1284p (cod CNCSIS: 140).	Capitol	1		12.500
	V.Neagoe, Rețele neurale pentru explorarea datelor, Editura Matrix Rom, București, 2018, ISBN: 978-606-25-0462-5, 173p (COD CNCSIS: 39).	Carte	1		50.000
	A1.2.1 Material didactic / Lucrări didactice publicate în edituri cu ISBN (Manuale didactice)	Tip [1]	Nr. Autori		
1					0.000
					0.000
	Total A1				**112.500**

Nr.crt.	A2 - Activitatea de cercetare				Punctaj
	A2.1 Articole în reviste cotate ISI, și lucrări în volumele unor manifestări științifice indexate ISI	Baza de date [4]	Nr. Autori	Factor impact [3] (conf. Top [10])	
1	V. Neagoe, "Inversion of the Van der Monde Matrix", IEEE Signal Processing Letters, vol. 3, (1996),pp. 119-120, **WOS:A1996UF76300008**	ISI-Q2	1	2.813	109.390
2	**V. E. Neagoe**, R. M. Stoica, A. I. Ciurea, L. Bruzzone, and F. Bovolo, "Concurrent Self-Organizing Maps for supervised/unsupervised change detection in remote sensing images,"IEEE J. Selected Topics Appl. Earth Obs. Remote Sens., vol. 7, no. 8, pp. 3525–3533, Aug. 2014, **WOS:000343055200031**.	ISI-Q2	5	2.777	21.662
3	**V. E. Neagoe,** "Predictive Ordering and Linear Approximation for Image Data Compression", IEEE Transactions on Communications,vol. 36, October, 1988, pp. 1179-1182.DOI: 10.1109/26.7539, **WOS:A1988Q056500015**	ISI-Q1	1	4.671	165.130
4	**V. E. Neagoe**, "Predictive ordering tehnique and feedback transform coding for data compression of still pictures", IEEE Trans Commun., vol. COM-40 (1992), pp. 386-396.**WOS:A1992HP27100017**	ISI-Q1	1	4.671	165.130
5	**V. Neagoe**, "Applying pattern recognition principles for intelligent detection of FSK signals", Signal Processing, Elsevier, Amsterdam-New York, vol. 32, (1993),p. 257-261, DOI: 10.1016/0165-1684(93)90045-C, **WOS:A1993LC15200013.**	ISI-Q1	1	3.470	129.100
6	**V. Neagoe**, "A two-dimensional nonuniform sampling expansion model", Signal Processing, Elsevier, Amsterdam-New York, vol. 33, (1993), pp. 1-21, **WOS:A1993MD67200001**.	ISI-Q1	1	3.470	129.100
7	**V. E. Neagoe,** "Chebyshev Nonuniform Sampling Cascaded by Discrete Cosine Transform for Optimum Interpolation", IEEE Transactions on Signal, Acoustics and Speech Processing (in present IEEE Transactions on Signal Processing), vol. 38, nr. 10, October 1990, pp. 1812-1816.**WOS:A1990EA28000021**	ISI-Q1	1	4.203	151.090
8	**V. Neagoe**, "A Neural Approach to Compression of Hyperspectral Remote Sensing Imagery", Proceedings of International Conference, 7th Fuzzy Days Dortmund, Germany, October 1-3, 2001. ISSN: 0302-9743.**WOS:000237080600045.**	ISI	1	0.250	32.500
9	**V. E. Neagoe,** A. Ropot, and A. Mugioiu, "Real Time Face Recognition Using Decision Fusion of Neural Classifiers in the Visible and Thermal Infrared Spectrum", Proc. of the 2007 IEEE International Conference on Advanced Video and Signal based Surveillance (AVSS 2007), London (United Kingdom), 5-7 September 2007, ISBN:978-1-4244-1696-7, **WOS:000255224900051.**	ISI	3	0.250	10.833
10	**V. E. Neagoe**, A. D. Ciotec, A. P. Bărar, "A Concurrent Neural Network Approach to Pedestrian Detection in Thermal Imagery", Proceedings of the 9th International Conference on Communications (COMM), June 21-23, 2012, Bucharest, Romania, pp. 133 - 136, ISBN : 978-1-4673-2573-8, **WOS:000307808200030.**	ISI	3	0.250	10.833
11	**V.E. Neagoe** and A. Ropot, "Concurrent Self-Organizing Maps - A Powerful Artificial Neural Tool for Biometric Technology", Proc. NATO Advanced Research Workshop on Data Fusion Technologies for Harbour Protection, June 27-July 01, 2005, Tallin (Estonia), published 2009, ISSN: 1871-4668, **WOS:000262044900034.**	ISI	2	0.250	16.250
12	**V. E. Neagoe** and A. Ropot, " A New Neural Approach for Pattern Recognition in Space Imagery", Proc. NATO Advanced Research Workshop on Data Fusion Technologies for Harbour Protection, June 27-July 01, 2005, Tallin (Estonia), published 2009, ISSN: 1871-4668, **WOS:000262044900033.**	ISI	2	0.250	16.250

13	**V. E. Neagoe**, A. Mugioiu, and I. Stanculescu, "Face Recognition using PCA versus ICA versus LDA cascaded with the Neural Classifier of Concurrent Self-Organizing Maps", Proceedings of the 8th Conference on Communications, Bucharest, June 10-12, 2010, vol. I, pp. 225-228, ISBN:978-1-4244-6363-3, **WOS:000299870700053**.	ISI	3	0.250	**10.833**
14	**V. E. Neagoe**, C.Tudoran, and M. Neghină, "A Neural Network Approach to Pedestrian Detection", Proceedings of the 13th WSEAS International Conference on Computers, Rhodes Island, Greece, July 23-25, 2009, pp. 374-379, ISBN: 978-960-474-099-4, **WOS:000276790600056.**	ISI	3	0.250	**10.833**
15	**V. E. Neagoe** and G. Strugaru, "Concurrent Neural Classifiers for Pattern Recognition in Multispectral Satellite Imagery", Proceedings of the 12th WSEAS Computer Conference, Heraklion, Crete Island, Greece, July 22-25, 2008, pp. 893-898, ISBN: 978-960-6766-85-5, **WOS:000260369300141.**	ISI	2	0.250	**16.250**
16	**V. E. Neagoe,** "New Self-Organizing Maps with Non-Conventional Metrics and their Applications for Iris Recognition and Automatic Translation", Proc. of the 11th WSEAS International Conference on Computers, Agios Nikolaos, Crete Island, Greece, 23-28 July 2007, pp. 145-150, ISBN: 978-960-8457-92-8, **WOS:000257859700027.**	ISI	1	0.250	**32.500**
17	**V. E. Neagoe** and A. Ropot, "Concurrent Self-Organizing Maps for Pattern Classification", Proc. of First IEEE International Conference on Cognitive Informatics, ICCI 2002, 19-20 August 2002, Calgary, Alberta, Canada, pp. 304-312, 0-7695-1724-2, **WOS:000177817600036.**	ISI	2	0.250	**16.250**
18	**V. E. Neagoe,** "Seeking pattern recognition principles for intelligent detection of FSK signals", Proc. of the 11th International Conference on Pattern Recognition, Aug. 30-Sep. 3, 1992, The Hague (The Netherlands), pp. 721-724, ISBN:0-8186-2915-0, **WOS:A1992BA37Z00171.**	ISI	1	0.250	**32.500**
19	**V. E. Neagoe**, C. E. Neghina, "Training label cleaning with ant colony optimization for classification of remote sensing imagery," 2015 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2015), Milano, Italy, July 26-31, 2015,pp. 421-424, IEEE Catalog Number: CFP15IGA-USB, ISBN:978-1-4799-7929-5, **WOS:000371696700107.**	ISI	2	0.250	**16.250**
20	**V. E. Neagoe**, S. V. Carata, A. D. Ciotec, "Automatic target recognition in SAR imagery using Pulse-Coupled Neural Network segmentation cascaded with virtual training data generation CSOM-based classifier," 2015 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2015), Milano, Italy, July 26-31, 2015, pp.3274-3277, IEEE Catalog Number: CFP15IGA-USB, 978-1-4799-7929-5, **WOS:000371696703092.**	ISI	3	0.250	**10.833**
21	**V. E. Neagoe,** A. Ciurea, L. Bruzzone, F. Bovolo, "A novel neural approach for unsupervised change detection using SOM clustering for pseudo-training set selection followed by CSOM classifier", 2014 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2014), Quebec City Q.C., Canada, July 2014, pp. 1437 – 1440, ISBN:978-1-4799-5775-0, **WOS:000349688102045.**	ISI	4	0.250	**8.125**
22	**V. E. Neagoe**, R. M. Stoica, "A new neural network-based approach for automatic annotation of remote sensing imagery," 2014 IEEE International Geoscience and Remote Sensing Symposium Proceedings (IGARSS 2014), Quebec City Q.C., Canada, July 2014, pp. 1781 – 1784, ISBN:978-1-4799-5775-0, **WOS:000349688102128.**	ISI	2	0.250	**16.250**
23	**V. E. Neagoe,** A. D. Ciotec, "A New Approach for Accurate Classification of Hyperspectral Images Using Virtual Sample Generation by Concurrent Self-Organizing Maps", Proc. IEEE International Geoscience & Remote Sensing Symposium, Melbourne, Australia, 21-26 July, 2013, pp. 1031-1034, ISBN 978-1-4799-1114-1, **WOS:000345638901040.**	ISI	2	0.250	**16.250**
24	**V. E. Neagoe**, R. M. Stoica and A. Ciurea, "A Modular Neural Model for Change Detection in Earth Observation Imagery", 2013 IEEE International Geoscience & Remote Sensing Symposium Proceedings (IGARSS 2013), Melbourne (Australia), 21-26 July, 2013, pp. 3321-3324, ISBN 978-1-4799-1114-1, **WOS:000345638903099.**	ISI	3	0.250	**10.833**
25	**V.E. Neagoe**, "Neural Network Models for Pattern Recognition in Satellite and Aerial Imagery with Environment and Defense Applications", Proc. International Conference on Communication and Management in Technological Innovation and Academic Globalization, Puerto De La Cruz, SPAIN, NOV 30-DEC 02, 2010, ISBN:978-960-474-254-7, **WOS:000291460100002.**	ISI	1	0.250	**32.500**
26	**V. E. Neagoe** and M. Neghina, "Face Detection in Color Images Using Fusion of the Chrominance and Luminance Channel Decisions", Proceedings of the 8th Conference on Communications, Bucharest, June 10-12, 2010, vol. I, pp. 229-232, ISBN:978-1-4244-6363-3, **WOS:000299870700054.**	ISI	2	0.250	**16.250**
27	**V. E. Neagoe**, I. Mitrache, and D. Cărăuşu, "3-D Face Recognition Using Concurrent Neural Modules", Proceedings of the 13th WSEAS International Conference on Computers, Rhodes Island, Greece, July 23-25, 2009, pp. 368-373, ISBN: 978-960-474-099-4, **WOS:000276790600055**.	ISI	3	0.250	**10.833**
28	**V. E. Neagoe** and A. Mugioiu, "A fully neural approach to color facial image recognition", Proc. of the World Automation Congress, 2008 (WAC 2008), International Symposium on Soft Computing in Industry (ISSCI'08),Sept. 28–Oct. 2, 2008, Hawaii, USA, ISBN:978-1-8893-3538-4, **WOS:000269081500119.**	ISI	2	0.250	**16.250**
29	**V. E. Neagoe** and G. Strugaru, "A concurrent neural network model for pattern recognition in multispectral satellite imagery", Proc. of the World Automation Congress, 2008 (WAC 2008), International Symposium on Soft Computing in Industry (ISSCI'08), Sept. 28–Oct. 2, 2008, Hawaii, USA, ISBN:978-1-8893-3538-4, **WOS:000269081500120.**	ISI	2	0.250	**16.250**
30	**V. E. Neagoe** and C. Tudoran, "Road following for autonomous vehicle navigation using a concurrent neural classifier", Proc. of the World Automation Congress, 2008 (WAC 2008), International Symposium on Soft Computing in Industry (ISSCI'08), Sept. 28–Oct. 2, 2008, Hawaii, USA, ISBN:978-1-8893-3538-4, **WOS:000269081500121.**	ISI	2	0.250	**16.250**
31	**V. E. Neagoe**, A. Mugioiu and C. Tudoran, "Concurrent Self-Organizing Maps for Multispectral Facial Image Recognition", Proc. of the 2007 IEEE Symposium on Computational Intelligence in Image and Signal Processing (CIISP 2007), April 1-5, 2007, Honolulu, Hawaii, USA, pp. 330-335, ISBN:978-1-4244-0707-1, **WOS:000252299800056.**	ISI	3	0.250	**10.833**
32	**V. E. Neagoe**, A. Ropot, "Concurrent self-organizing maps - a powerful artificial neural tool for biometric technology", Proc. 5th International Symposium on Soft Computing for Industry held at the 6th Biannual World Automation Congress, Seville, June 28-July 01, 2004, ISBN: 1-889335-23-1, **WOS:000230424800044.**	ISI	2	0.250	**16.250**
33	**V. E. Neagoe**, R., Iatan, I. F. Iatan, "A Nonlinear Neuro-Fuzzy Model for Prediction of Daily Exchange Rates", Proc. 5th International Symposium on Soft Computing for Industry held at the 6th Biannual World Automation Congress WAC'04, Seville, June 28-July 01, 2004, ISBN: 1-889335-23-1, IEEE Catalog 04EX832C, **WOS:000230424800089.**	ISI	3	0.250	**10.833**
34	S. Grunwald, **V. E. Neagoe**, "A New Information-Theoretical Model for the Performance Evaluation in Breast Cancer Imagery", Proc. of the 25-th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Sept. 17-21, 2003, Cancun, Mexico, pp. 986-989, IEEE Press, ISBN:0-7803-7789-3, **WOS:000189395300259**.	ISI	2	0.250	**16.250**
35	**V. E. Neagoe** and I. Iatan, "A Neuro-Fuzzy Approach to Face Recognition", Proc. of 6th World Multiconference on Systemics, Cybernetics and Informatics (SCI 2002), 14-18 July 2002, Orlando, Florida, vol. XIV, pp. 120-125, ISBN 980-07-8147-1, **WOS:000178906400023**.	ISI	2	0.250	**16.250**

36	**V. E. Neagoe** and A. Ropot, "Concurrent Self-Organizing Maps for Classification of Multispectral Satellite Imagery", Proc. of 6th World Multiconference on Systemics, Cybernetics and Informatics (SCI 2002), 14-18 July 2002, Orlando, Florida, pp. 126-131. vol. XIV, ISBN 980-07-8147-1, **WOS:000178906400024.**	ISI	2	0.250	**16.250**
37	**V. E. Neagoe** and I. Iatan, "Face Recognition Using a Fuzzy-Gaussian Neural Network", Proc. of First IEEE International Conference on Cognitive Informatics, ICCI 2002, 19-20 August 2002, Calgary, Alberta, Canada, pp. 361-368, ISBN:0-7695-1724-2, **WOS:000177817600043.**	ISI	2	0.250	**16.250**
38	**V. Neagoe**, M. Vâlcu, and B. Sabac, "A Neural Approach for Detection of Road Direction in Autonomous Navigation", in "Computational Intelligence: Theory and Applications", editor: Bernd Reusch, pp. 324-333, Springer-Verlag, Berlin, ISSN: 0302-9743., **WOS:000237352100038.**	ISI	3	0.250	**10.833**
39	**V.E. Neagoe**, I. Fratila, "A Neural Segmentation of Multispectral Satellite Images", in "Computational Intelligence: Theory and Applications", editor: Bernd Reusch, pp. 324-333, Springer-Verlag, Berlin, ISSN: 0302-9743. **WOS:000237352100039.**	ISI	2	0.250	**16.250**
40	**V. Neagoe**, „Legendre descriptors for classification of polygonal closed curves", Proc. of the 11th International Conference on Pattern Recognition, Aug. 30-Sep. 3, 1992, The Hague (The Netherlands),pp. 717-720, ISBN:0-8186-2915-0, **WOS:A1992BA37Z00170.**	ISI	1	0.250	**32.500**
41	V. Neagoe, " Spectral Estimation Using Chebyshev Nonuniform Sampling in the Time and Frequency Domains", Proc. 5th European Signal Processing Conf (EUSIPCO-90), Sep. 18-21, 1990, Barcelona, Spain, pp. 461-464, ISBN:0-444-88636-2, **WOS:A1990BU04A00102.**	ISI	1	0.250	**32.500**
42	**V.E. Neagoe**, A. D. Ciotec, S.V. Carata, „A new multispectral pixel change detection approach using pulse-coupled neural networks for change vector analysis, "Proc. 2016 IEEE International Geoscience and Remote Sensing Conference (IGARSS 2016), Beijing, China, July 10-15, 2016, pp. 3386-3389, **WOS:000388114603102**, ISBN:978-1-5090-3332-4, ISSN: 2153-6996.	ISI	3	0.250	**10.833**
43	**V. E. Neagoe**, V. Chirila-Berbentea, "Improved Gaussian Mixture Model with Expectation-Maximization for Clustering of Remote Sensing Imagery", *Proc. 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2016),* Beijing, China, July 10-15, 2016, pp. 3063-3065, **WOS:000388114603021, ISBN**:978-1-5090-3332-4, **ISSN**: 2153-6996.	ISI	2	0.250	**16.250**
44	**V. E. Neagoe** and C. E. Neghina, "Feature Selection with Ant Colony Optimization and its Applications for Pattern Recognition in Space Imagery", *Proc. 11th International Conference on Communications (COMM 2016),* Bucharest, Romania, June 9-11, 2016, pp. 101–104, **WOS:000383221900022**, **ISBN**:978-1-4673-8197-0.	ISI	2	0.250	**16.250**
45	S. V. Carata, **V. E. Neagoe**, „A Pulse-Coupled Neural Network Approach for Image Segmentation and Its Pattern Recognition Application,"Proc. 11th International Conference on Communications (COMM 2016), June 9-11, 2016, pp. 61-64, **WOS:000383221900013**, ISBN:978-1-4673-8197-0.	ISI	2	0.250	**16.250**
46	**V.E. Neagoe**, V. Chirilă-Berbentea, "A novel approach for semi-supervised classification of remote sensing images using a clustering-based selection of training data according to their GMM responsibilities,"Proceedings of 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, Texas, USA, July 23–28, 2017, pp. 4730-4733, **WOS:000426954604195**, **DOI: 10.1109/IGARSS.2017.8128058**, ISBN:978-1-5090-4951-6, ISSN: 2153-6996; Electronic ISSN: 2153-7003.	ISI	2	0.250	**16.250**
47	**V.E. Neagoe**, C. E. Neghina, V. Chirila-Berbentea, "A genetic algorithm approach to purify the classifier training labels for the analysis of remote sensing imagery,"Proceedings of 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, Texas, USA, July 23–28, 2017, pp. 3234-3237, **WOS:000426954603081**, **DOI:10.1109/IGARSS.2017.8127686**, ISBN:978-1-50904951-6, ISSN: 2153-6996, Electronic ISSN: 2153-7003.	ISI	3	0.250	**10.833**
48	**V. E. Neagoe**, S.V. Carata, "Drunkenness diagnosis using a neural network-based approach for analysis of facial images in the thermal infrared spectrum, "Proceedings of 2017 E-Health and Bioengineering Conference (EHB)," Sinaia, Romania, June 22-24, 2017, pp. 165-168, **WOS:000445457500042**, ISBN:978-1-5386-0358-1, ISSN: 2575-5137, eISSN: 2575-5145.	ISI	2	0.250	**16.250**
49	**V. E. Neagoe**, R.M. Stoica, "A New Neural Approach of Supervised Change Detection in SAR Images Using Training Data Generation with Concurrent Self-Organizing Maps," *Proc. International Geoscience and Remote Sensing Symposium (IGARSS 2018),* Valencia, Spain, July 23-27 2018, pp. 4792-4795, **WOS:000451039804182**, ISBN:978-1-5386-7150-4, ISSN: 2153-6996.	ISI	2	0.250	**16.250**
50	**V.E. Neagoe**, A.D. Ciotec, "Supervized Change Detection for SAR Imagery based on Processing of a Low Size Training Data Set by an Ensemble of Self-Organizing Maps," *Proc. International Conference on Communications (COMM2018),* 14-16 June 2018, Bucharest, pp. 139-142, **WOS:000449526000025**, ISBN:978-1-5386-2350-3, ISSN: 1550-3607.	ISI	2	0.250	**16.250**
51	**V.E. Neagoe**, A.D. Ciotec, G.S. Cucu, "Deep Convolutional Neural Networks versus Multilayer Perceptron for Financial Prediction," *Proc. International Conference on Communications (COMM2018)* , 14-16 June 2018, Bucharest, pp. 201-206, **WOS:000449526000037**, ISBN:978-1-5386-2350-3, ISSN: 1550-3607.	ISI	3	0.250	**10.833**
52	**V.E. Neagoe**, A.D. Ciotec, G.S. Cucu, "Deep Convolutional Neural Networks versus Multilayer Perceptron for Financial Prediction," *Proc. International Conference on Communications (COMM2018)* , 14-16 June 2018, Bucharest, pp. 201-206, **WOS:000449526000037**, ISBN:978-1-5386-2350-3, ISSN: 1550-3607.	ISI	3	0.250	**10.833**
53	**V.E. Neagoe**, C.E Neghina, "An Artificial Bee Colony Approach for Classification of Remote Sensing Imagery," *Proc. of the 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI2018)* , 28-30 June 2018, Iasi, Romania, **WOS:000467734100151**, ISBN:978-1-5386-4901-5, ISSN:1843–2115.	ISI	2	0.250	**16.250**
54	V.C. Chirila-Berbentea, **V.E. Neagoe**, "Semi-Supervized Hyperspectral Image Classification using Virtually Labeled Training Data based on the Improved Gaussian Mixture Clustering," *Proc. of the 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI2018)* , 28-30 June 2018, Iasi, Romania, **WOS:000467734100084**, ISBN:978-1-5386-4901-5, ISSN:1843–2115.	ISI	2	0.250	**16.250**
	… Includeţi WOS: şi DOI:			0.000	**0.000**
	A2.2 Articole în reviste, şi în volumele unor manifestari stiintifice indexate în alte baze de date internationale recunoscute (BDI) [4]	Baza de date [4]	Nr. Autori		

1	**V. Neagoe,** "Using Legendre Polynomials to Introduce a New Orthogonal Transform for Significant Feature Selection", Proc. of the Pattern Recognition and Image Processing Conference, Las Vegas – Nevada, June 13-17, 1982, pp. 177-182.	Scopus	1		20.000
2	**V. Neagoe**, "Predictive Data Compression of Color Picture Signals Using a Component Coding Method", Proc. of the IEEE International Conference on Communications, Denver-Colorado, June 14-17, 1981.	Scopus	1		20.000
3	**V. Neagoe**, "Optimal M-ary System with Polynomial Form Pulse Code Modulation", Proc. of the IEEE Canadian Conference on Communications and Energy, Montréal, October 13-15, 1982.	Scopus	1		20.000
4	**V. Neagoe,** S. Grunwald, G. Muller, and A. Voiculescu, "Ischemic Heart Disease Diagnosis Using Classification of ECG Spectral Patterns", Proc. of the Seventh International Conference on Pattern Recognition, Montréal, July 30-August 2 Sept. 1984, pp. 972-974	Scopus	4		5.000
5	**V. E. Neagoe,** "An optimum 2D color space for pattern recognition", Proc. of the 2006 International Conference on Image Processing, Computer Vision&Pattern Recognition, Las Vegas, Nevada, June 26-29, 2006, vol. 2, pp. 526-532, ISBN: 1-932415-99-8.	Scopus	1		20.000
6	**V. Neagoe,** "Decorrelation of the Color Space, Feature/Decision Fusion, and Concurrent Neural Classifiers for Color Pattern Recognition", The 2008 World Congress in Computer Science, Computer Engineering, and Applied Computing (WORLDCOMP'08), International Conference on Image Processing, Computer Vision & Pattern Recognition (ICPV'08), July 14-17, 2008, Las Vegas, Nevada, USA., pp. 28-34, CSREA Press Number 07EX 1573C, ISBN 1-60132-076-0, 1-60132-077-9 (1-60132-078-7).	Scopus	1		20.000
7	**V. E. Neagoe,** J. Mitrache, and S. Preotesoiu, "Feature-Based Face Recognition Approach Using Gabor Wavelet Filters cascaded with Concurrent Neural Modules", World Automation Congress (WAC 2006), July 24-26, 2006, Budapest, ISBN 1-889-335-32-0, TSI Press, San Antonio, Texas, USA.	IEEE Explore	3		6.667
8	**V. E. Neagoe,** C. Tudoran, and G. Strugaru, "A Neural Data Fusion Model for Hydrological Forecasting", World Automation Congress (WAC 2006), July 24-26, 2006, Budapest, ISBN 1-889-335-32-0, TSI Press, San Antonio, Texas, USA.	IEEE Explore	3		6.667
9	**V. E. Neagoe**, M. Neghina, M. Datcu, "Neural Network Techniques for Automated Land-Cover Change Detection in Multispectral Satellite Time Series Imagery", International Journal of Mathematical Models and Methods in Applied Sciences, Issue 1, Volume 6, 2012, pp. 130-139, ISSN: 19980140, NAUN Press.	Scopus	3		6.667
10	E. C. Neghină**, V. E. Neagoe,** R. M. Stoica and A. D. Ciotec, "Neural and Ant Colony Optimization versus Statistical Models for Supervised Classification of Multispectral Remote-Sensing Imagery", Scientific Bulletin of the Polytechnic University of Bucharest, Series C, Vol. 75, Iss. 3, 2013, pp. 87-100, ISSN 2286-3540.	Scopus	4		5.000
11	A. D. Ciotec, **V. E. Neagoe**, A. P. Bărar, "Concurrent Self-Organizing Maps for Pedestrian Detection in Thermal Imagery", Scientific Bulletin of the Polytechnic University of Bucharest, Series C, Vol. 75, Iss. 4, 2013, ISSN 2286-3540.	Scopus	3		6.667
12	**V.E. Neagoe**, C.T. Tudoran, "A Neural Machine Vision Model for Road Detection in Autonomous Navigation", University Politehnica of Bucharest, Scientific Bulletin Series C - Electrical Engineering, No 2, 2011, pp. 167178.	Scopus	2		10.000
13	**V. E. Neagoe** and A. Ciotec, Subject-Independent Emotion Recognition from Facial Expressions using a Gabor Feature RBF Neural Classifier Trained with Virtual Samples Generated by Concurrent Self-Organizing Maps, Proceedings of the 11th WSEAS International Conference On SIGNAL PROCESSING, COMPUTATIONAL GEOMETRY And ARTIFICIAL VISION (ISCGAV '11), pp. 266 – 271, ISBN: 978-1-61804-027-5.	Scopus	2		10.000
14	**V. E. Neagoe**, M. Neghina, and M. Datcu, A Neural Network Approach for Land-Cover Change Detection in Multi-Temporal Multispectral Remote-Sensing Imagery, Proceedings of the 11th WSEAS International Conference on SIGNAL PROCESSING, COMPUTATIONAL GEOMETRY And ARTIFICIAL VISION (ISCGAV '11), pp. 266 – 271, ISBN: 978-1-61804-027-5	Scopus	3		6.667
15	C. Tudoran and **V. Neagoe,** "A New Neural Network Approach for Visual Autonomous Road Following", Latest Trends on Computers (Proceedings of the 14th WSEAS International Conference on Computers), Corfu Island, Greece, July 23-25, 2010, pp. 266-271, ISBN: 978-960-474-201-1.	Scopus	2		10.000
16	**V. Neagoe** and M. Neghina, "Face Detection Using A Dual Cross-Validation of Chrominance/Luminance Channel Decisions and Decorrelation of the Color Channel", Latest Trends on Computers (Proceedings of the 14th WSEAS International Conference on Computers), Corfu Island, Greece, July 23-25, 2010, pp. 391-396, ISBN: 978-960-474-201-1.	Scopus	2		10.000
17	R. M. Stoica, **V. E. Neagoe**, "Self-Organizing Map for clustering of remote sensing imagery," Scientific Bulletin of the Polytechnic University of Bucharest, Series C, Vol. 76, Iss. 1, 2014, pp. 69-80, ISSN 2286-3540	Scopus	2		10.000
18	**V. Neagoe**, C. Neghina, and M. Neghina, "Ant Colony Optimization for Logistic Regression and Its Application to Wine Quality Assessment", Proceedings of the International IEEEAM Conference on Mathematical Models for Engineering Science (MMES'10), Tenerife (Spain), November 30-December 2, 2010, vol. I, pp. 195-200, ISBN: 978-960-474-252-3	Scopus	3		6.667
19	**V. Neagoe** and A. Ciotec, "Virtual Sample Generation Using Concurrent-Self-Organizing Maps and Its Application for Facial Expression Recognition", Proceedings of the International IEEEAM Conference on Mathematical Models for Engineering Science (MMES'10), Tenerife (Spain), November 30-December 2, 2010, vol. I, pp. 167-181, ISBN: 978-960-474-252-3.	Scopus	2		10.000
20	C. Tudoran and **V. Neagoe**, "A New Neural Network Approach for Visual Autonomous Road Following", Latest Trends on Computers (Proceedings of the 14th WSEAS International Conference on Computers), Corfu Island, Greece, July 23-25, 2010, pp. 266-271, ISBN: 978-960-474-201-1.	Scopus	2		10.000
21	**V. Neagoe**, D. Carausu, and G. Strugaru, "A Concurrent Neural Module Classifier for Automated Target Recognition in SAR Imagery ", Latest Trends on Computers (Proceedings of the 14th WSEAS International Conference on Computers), Corfu Island, Greece, July 23-25, 2010, pp. 208-213, ISBN: 978-960-474-201-1	Scopus	3		6.667
22	**V. Neagoe**, C.Tudoran, and M. Neghină, "A Neural Network Approach to Pedestrian Detection", Proceedings of the 13th WSEAS International Conference on Computers, Rhodes Island, Greece, July 23-25, 2009, pp. 374-379, ISBN: 978-960-474-099-4.	Scopus	3		6.667
23	**V. Neagoe** and G. Strugaru, "Concurrent Neural Classifiers for Pattern Recognition in Multispectral Satellite Imagery", Proceedings of the 12th WSEAS Computer Conference, Heraklion, Crete Island, Greece, July 22-25, 2008, pp. 893-898, ISBN: 978-960-6766-85-5. V	Scopus	2		10.000

24	**V. E. Neagoe**, “An optimum 2D color space for pattern recognition”, Proc. of the 2006 International Conference on Image Processing, Computer Vision&Pattern Recognition, Las Vegas, Nevada, June 26-29, 2006, vol. 2, pp. 526-532, ISBN: 1-932415-99-8.	Scopus	1		**20.000**
25	**V. E. Neagoe,** “Color Space Projection, Feature Fusion and Concurrent Neural Modules for Biometric Image Recognition”, Proc. of the 5th WSEAS International Conference on Computational Intelligence, Man-Machine Systems And Cybernetics (CIMMACS '06), Venice, Italy, November 20-22, 2006, ISBN: 960-8457-56-4; ISSN: 1790-5117.	Scopus	1		**20.000**
	… includeţi DOI: dacă există				**0.000**
	A2.3.1 Proprietate intelectuală, brevete de inventie, certificate ORDA - internationale [5]	Înregistrat la [5]:	Nr. Autori	Factor impact [12]	
1				0.000	**0.000**
	… includeţi WOS: dacă există			0.000	**0.000**
	A2.3.2 Proprietate intelectuală, brevete de inventie, certificate ORDA - nationale (OSIM)	Înregistrat la [5]:	Nr. Autori	Factor impact [12]	
1	**V. Neagoe**, “Metodă şi sistem de traducere automată cu corecţie a erorilor de tastare utilizând o reţea neuronală sintactică cu autoorganizare”, Brevet de invenţie, nr. 116684B1/30.03.2001, OSIM, Romania.		1	0.500	**25.000**
2	**V. Neagoe**, “Dispozitiv diferential neliniar pentru conversia digitala cu compresie de spectru a semnalelor de televiziune”, Brevet de inventie nr. 73603/1978, OSIM, Romania.		1	0.500	**25.000**
3	**V. Neagoe**, “Metoda sisistem de transmisiune multipla prin modulatie “n+1”-dimensionala in cod de impulsuri de forma polinomiala”, Brevet de inventie nr. 70645/1978, OSIM, Romania.		1	0.500	**25.000**
4	**V. Neagoe**, “Metoda si dispozitiv de codare optimala a semnalelor video prin modulatie delta adaptiva cu sistem de dubla predictie”, Brevet de inventie nr. 70594/1977, OSIM, Romania.		1	0.500	**25.000**
5	**V. Neagoe**, “Metoda si dispozitiv de transmisiune M-ary prin modulatie log2(n+1)-dimensionala in cod de impulsuri de forma polinomiala”, Brevet de inventie nr. 69568/1977, OSIM, Romania.		1	0.500	**25.000**
6	A. Spataru, **V. Neagoe**, “Modulator delta adaptiv pentru codarea semnalelor video”, Brevet de inventie nr. 63977/1976, OSIM, Romania.		2	0.500	**12.500**
	… includeţi WOS: dacă există			0.000	**0.000**
	A2.4.1.1 Granturi / proiecte de cercetare câştigate prin competiţie [6] sau Contracte cu agenţi economici în valoare de minim 10.000 dolari SUA echivalent încasaţi [6] (Director / responsabil partener) - internaţionale	[6]	Nr.ani		
1					**0.000**
	… includeţi perioada desfăşurării: , identificare				**0.000**
	A2.4.1.2 Granturi / proiecte de cercetare câştigate prin competiţie [6] sau Contracte cu agenţi economici în valoare de minim 10.000 dolari SUA echivalent încasaţi [6] (Director / responsabil partener) - naţionale		Nr.ani		
1	**V. Neagoe (director proiect)**, Sistem multiplu de identificare biometrica pentru prevenirea terorismului – SIB, (Program CEEX), contract 17-06-17/UPB, Beneficiar direct : Optoelectronica 2001 SA; Beneficiar final: Agentia Spatiala Romana, (2006-2009)		4.00		**40.000**
2	**V. Neagoe (director grant)**, Infrastructura modulara pentru sistem de acces utilizand parametri biometrici – FACE&IRIS RECOGNITION – FAIR (Programul National Securitate), nr. 17-06-01/UPB, Beneficiar: Agentia Spatiala Romana, (2005-2006)		2.00		**20.000**
3	**V. Neagoe (director grant)**, Module neuronale autoorganizabile pentru recunoasterea formelor (Grant cu Academia Romana, nr. 171/2003 – Acad. Romana, nr. 17-03-06/UPB), (2003-2004)		2.00		**20.000**
4	**V. Neagoe (director grant)**, Sistem neural expert pentru recunoasterea formelor in imageria satelitara (Contract de cercetare cu Agentia Nationala pentru Stiinta, Tehnologie si Inovare (ANSTI), nr. Contract Adit. 351/1999/II – ANSTI (MCT), nr. 17-96-04/UPB); Beneficiar: Agentia Spatiala Romana, (1996-1999)		4.00		**40.000**
5	**V. Neagoe (director grant)**, Compresia secventelor de imagini (Contract de cercetare cu Agentia Nationala pentru Stiinta, Tehnologie si Inovare (ANSTI), tema A23/1999 inclusa in contractul nr. 836/96 – ANSTI (MCT)); Beneficiar: Agentia Spatiala Romana, (1997-1999)		3.00		**30.000**
6	**V. Neagoe (director grant)**, Retele neurale pentru compresia si segmentarea imaginilor color (Contract cu Ministerul Educatiei Nationale),(1997-1998)		2.00		**20.000**
7	**V. Neagoe (director grant)**, Retele neurale pentru robotica vehiculara (Contract cu Ministerul Cercetarii si Tehnologiei), (1996-1998)		3.00		**30.000**
8	**V. Neagoe (director grant)**, Recunoasterea formelor cu aplicatii in imageria satelitara (Beneficiar: Agentia Spatiala Romana), (1994-1996)		3.00		**30.000**
9	**V. Neagoe (director grant)**, Compresia de date pentru imageria satelitara (Beneficiar: Agentia Spatiala Romana), (1993-1994)		2.00		**20.000**
	… includeţi perioada desfăşurării: , identificare				**0.000**
	A2.4.2.1 Granturi / proiecte de cercetare câştigate prin competiţie [6] sau Contracte cu agenţi economici în valoare de minim 10.000 dolari SUA echivalent încasaţi [6] în calitate de director sau responsabil contract (Membru în echipă) - internaţionale		Nr.ani		
1					**0.000**
	… includeţi perioada desfăşurării: , identificare				**0.000**

			Nr.ani		
	A2.4.2.2 Granturi / proiecte de cercetare câştigate prin competiţie [6] sau Contracte cu agenţi economici în valoare de minim 10.000 dolari SUA echivalent încasaţi [6] în calitate de director sau responsabil contract (Membru în echipă) - naţionale				
1					**0.000**
	… includeţi perioada desfăşurării: , identificare				**0.000**
	Total A2			**40.825**	**2318.727**

Nr.crt.	A3 - Recunoașterea și impactul activității				
	A3.1.1 Citări [7] în cărţi, reviste și volume ale unor manifestări științifice - cărți, ISI [8]	Baza de date	Nr. Autori articol citat	[7], [8]	**Punctaj**
	V.E. Neagoe, "Chebyshev Nonuniform Sampling Cascaded by Discrete Cosine Transform for Optimum Interpolation", *IEEE Transactions on Signal, Acoustics and Speech Processing*, vol. 38, nr. 10, October 1990, pp. 1812-1816.		1.00		
1	A New Method for Chebyshev Polynomial Interpolation Based on Cosine Transforms By: Li, Bing-Zhao; Zhang, Yan-Li; Wang, Xian; et al. CIRCUITS SYSTEMS AND SIGNAL PROCESSING, Volume: 35, Issue: 2, Pages: 719•729, Published: JAN 2016.	ISI	1		**8.000**
2	Forecasting the underlying potential governing the time series of a dynamical system By: Livina, V. N.; Lohmann, G.; Mudelsee, M.; et al. PHYSICA A•STATISTICAL MECHANICS AND ITS APPLICATIONS, Volume: 392, Issue: 18, Pages: 3891•3902, Published: SEP 15 2013.	ISI	1		**8.000**
3	Approximate Signal Reconstruction Using Nonuniform Samples in Fractional Fourier and Linear Canonical Transform Domains By: Sharma, K. K. IEEE TRANSACTIONS ON SIGNAL PROCESSING, Volume: 57, Issue: 11, Pages: 4573•4578, Published: NOV 2009.	ISI	1		**8.000**
4	CONTINUOUS GNSS ORBIT CONSTRUCTION USING INTERPOLATION AND NEURAL NETWORK APPROXIMATION APPROACH By: Preseren, Polona Pavlovcic; Sterle, Oskar; Kuhar, Miran; et al. Edited by: Stirn, LZ; Zerovnik, J; Drobne, S; et al. Conference: 10th International Symposium on Operational Research Location: Nova Gorica, SLOVENIA Date: SEP 23-25, 2009, Sponsor(s): Austrian Sci res Liason Office, Dept Ljubljana; Novo Mesto, Fac Info Studies; HIT, Nova Gorica; Slovenian Res Agency, Repub Slovenia, PROCEEDINGS OF THE 10TH INTERNATIONAL SYMPOSIUM ON OPERATIONAL RESEARCH SOR 09, Pages: 101•110,Published: 2009.	ISI	1		**8.000**
5	Chebyshev interpolation for DMT modems By: Cuypers, G; Ysebaert, G; Moonen, M; et al., Book Group Author(s): IEEE Conference: IEEE International Conference on Communications (ICC 2004) Location: Paris, FRANCE Date: JUN 20-24, 2004, Sponsor(s): IEEE; Alcatel; France Telecom; Cegetel Grp; Thales; Bouygues Telecom; Siemens; Siemens Mobile; Mitsubishi; GET; IEEE Commun Soc; EUREL; ICC GLOBECOM; See 2004 IEEE INTERNATIONAL CONFERENCE ON COMMUNICATIONS, VOLS 1•7, Pages: 2736•2740, Published: 2004.	ISI	1		**8.000**
6	Non•uniform sampling issues arising in shallow angle wave profiling LIDAR By: Belmont, MR; Horwood, JMK; Thurley, RWF Edited by: Rizoli, JA Conference: 7th IEEE/OES Working Conference on Current Measurement Technology Location: SAN DIEGO, CA Date: MAR 13•15, 2003, Sponsor(s): Ocean Engn Soc, Current Measurement Technol Comm; IEEE, Current Measurement Technol Comm PROCEEDINGS OF THE IEEE/OES SEVENTH WORKING CONFERENCE ON CURRENT MEASUREMENT TECHNOLOGY, Pages: 135•139, Published: 2003.	ISI	1		**8.000**
7	On computing Chebyshev optimal nonuniform interpolation By: Wang, ZD; Jullien, GA; Miller, WC SIGNAL PROCESSING, Volume: 51, Issue: 3, Pages: 223•228 Published: JUN 1996.	ISI	1		**8.000**
8	An Extension of Nyquists Theorem to Nonuniformly Sampled Finite•Length Data By: Belmont, MR INTERNATIONAL JOURNAL OF ADAPTIVE CONTROL AND SIGNAL PROCESSING, Volume: 9, Issue: 2, Pages: 163•181, Published: MAR•APR 1995.	ISI	1		**8.000**
	… includeti WOS:, editura dacă există				**0.000**
	V. Neagoe, "Inversion of the Van der Monde Matrix", *IEEE Signal Processing Letters* , vol. 3, (1996), 119-120.				**Punctaj**
1	A recursive algorithm for computing the inverse of the Vandermonde matrix By: YA. Ghassabeh Cogent Engineering, Volume:3, Issue: 1, 2016, WOS:000397384100015, ISSN: 2331-1916.	ISI	1		**8.000**
2	Robustness analysis of a hybrid of recursive neural dynamics for online matrix inversion By: Chen, Ke; Yi, Chenfu APPLIED MATHEMATICS AND COMPUTATION, Volume: 273, Issue C, Pages: 969•975, Published: JAN 15 2016, WOS:000365613400085, ISSN: 0096-3003, eISSN: 1873-5649.	ISI	1		**8.000**
3	Velocity of excitations in ordered, disordered, and critical antiferromagnets By: Sen, Arnab; Suwa, Hidemaro; Sandvik, Anders W. PHYSICAL REVIEW B, Volume: 92, Issue: 19 Article Number: 195145, Published: NOV 23 2015.	ISI	1		**8.000**
4	Generalized Moment Method for Gap Estimation and Quantum Monte Carlo Level Spectroscopy By: Suwa, Hidemaro; Todo, Synge PHYSICAL REVIEW LETTERS, Volume: 115, Issue: 8, Article Number: 080601, Published: AUG 17 2015.	ISI	1		**8.000**

5	A New Derivation and Recursive Algorithm Based on Wronskian Matrix for Vandermonde Inverse Matrix By: Zhou, Qun; Zhang, Xinjian; Liu, Xiongwei MATHEMATICAL PROBLEMS IN ENGINEERING, Article Number: 924757, Published: 2015.	ISI	1		8.000
6	On the Computation of the Determinant of a Generalized Vandermonde Matrix By: Kitamoto, Takuya Edited by: Gerdt, VP; Koepf, W; Seiler, WM; et al. Conference: 16th International Workshop on Computer Algebra in Scientific Computing (CASC) Location: Warsaw, POLAND Date: SEP 08-12, 2014, Sponsor(s): Univ Kassel, Inst Math; Warsaw Univ Life Sci, Fac Appl Informat & Math, COMPUTER ALGEBRA IN SCIENTIFIC COMPUTING, CASC 2014, Book Series: Lecture Notes in Computer Science, Volume: 8660, Pages: 242•255, Published: 2014.	ISI	1		8.000
7	Multichannel Sampling of Signals Band•Limited in Offset Linear Canonical Transform Domains By: Xiang, Qiang; Qin, Kai-Yu; Huang, Qin-Zhen CIRCUITS SYSTEMS AND SIGNAL PROCESSING, Volume: 32, Issue: 5, Pages: 2385•2406, Published: OCT 2013.	ISI	1		8.000
8	Recurrent implicit dynamics for online matrix inversion By: Chen, Ke APPLIED MATHEMATICS AND COMPUTATION, Volume: 219, Issue: 20, Pages: 10218•10224, Published: JUN 15 2013.	ISI	1		8.000
9	New method and circuit for processing of band•limited periodic signals By: Petrovic, Predrag B. SIGNAL IMAGE AND VIDEO PROCESSING, Volume: 6, Issue: 1, Pages: 109•123, Published: MAR 2012.	ISI	1		8.000
10	Sobolev type inequalities of time•periodic boundary value problems for Heaviside and Thomson cables By: Takemura, Kazuo; Kametaka, Yoshinori; Watanabe, Kohtaro; et al. BOUNDARY VALUE PROBLEMS, Pages: 1•15, Published: 2012.	ISI	1		8.000
11	A Highly Accurate Multi•Scale Full/Half•Order Polynomial Interpolation By: Liu, Chein•Shan CMC•COMPUTERS MATERIALS & CONTINUA, Volume: 25, Issue: 3, Pages: 239•263, Published: OCT 2011.	ISI	1		8.000
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Chebyshev nonuniform sampling cascaded with the discrete cosine transform for optimum interpolation

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It follows, therefore, that the sequence of reflection coefficients in (1) has a predictor polynomial with all of its roots on a circle of radius $|\rho|$.

IV. Conclusions

Decaying geometric sequences of reflection coefficients arise from Gaussian-shaped autocorrelation functions. It has now been shown that such reflection coefficient sequences have predictor polynomials with all roots on a circle centered at the origin of radius $|\rho|$ where ρ is the ratio of two consecutive terms in the reflection coefficient sequence.

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Chebyshev Nonuniform Sampling Cascaded with the Discrete Cosine Transform for Optimum Interpolation

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***Abstract*—This correspondence presents a new method for discrete representation of signals $\{g(t), t \in [0, L], g \in \mathcal{L}^2(0, L)\}$ consisting of a cascade having two stages: a) nonuniform sampling according to Chebyshev polynomial roots; and b) discrete cosine transform applied on the nonuniformly taken samples. We have proved that the considered signal samples and the coefficients of the corresponding Chebyshev polynomial finite series are essentially a discrete cosine transform pair. It provides a method for fast computation of the coefficients of the optimum interpolation formula (which minimizes the maximum instantaneous error). If the signal $g(t)$ is band limited and has a finite energy, we deduce the condition of convergence for interpolation.**

Introduction

The Shannon sampling theorem and its variants [2], [8], [14] are well known as performing the reconstruction of a band-limited signal from the knowledge of its uniformly taken samples. There are also a few approaches to signal reconstruction from nonuniformly spaced samples [6], [8], [10]-[12]. The classical results of function interpolation theory in computational mathematics [4], [7] show that the best choice of interpolation points to minimize the maximum modulus of the instantaneous error corresponds to the roots of the Chebyshev polynomials of the first kind.

Recently, considerable attention has been paid to the use of orthogonal transforms applied to the uniformly spaced samples. These transforms concentrate the signal energy in the "low generalized frequency" spectrum and have applications for data compression and feature extraction in pattern recognition. If we consider data compression ability as a criterion, one of the best orthogonal transforms having a fast algorithm available was proved to be the discrete cosine transform introduced by Ahmed *et al.* [1], [2].

Based on the classical theory of interpolation and quadrature formulas, we have built a model of discrete representation of signals, consisting of a cascade of Chebyshev nonuniform sampling (CNS) followed by the discrete cosine transform (DCT). It provides a method for fast computation of the coefficients of the optimum interpolation formula for a given signal $\{g(t), t \in [0, L], g \in \mathcal{L}^2(0, L)\}$.

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Chebyshev Nonuniform Sampling and Discrete Cosine Transform

Theorem: Consider a real-valued signal $\{g(t), t \in [0, L], g \in \mathcal{L}^2(0, L)\}$. Choose the nonuniform sampling grid vector $t_N = (t_j)_{j=0}^{N-1}$ given by

$$t_j = (L/2)(1 + x_j), \quad 0 \le j \le N - 1 \tag{1}$$

where x_j represent the roots of the Nth degree Chebyshev polynomial of the first kind, i.e.,

$$x_j = -\cos\frac{(2j+1)}{2N}\pi = \cos\frac{2(N-j)-1}{2N}\pi$$
$$j = 0, 1, \cdots, N-1 \tag{2}$$

$(-1 < x_0 < x_1 \cdots < x_{N-1} < 1)$.

Consider the matrix $\boldsymbol{\psi}^{\text{DCT}} = (\psi_{hj}) 0 \le h \le N-1; 0 \le j \le N-1$ characterizing the discrete cosine transform as

$$\psi_{hj} = \sqrt{\frac{2}{N}}\, k(h) \cos\left[\frac{(2j+1)h\pi}{2N}\right] = \sqrt{\frac{2}{N}}\, \tilde{T}_h(x_j) \tag{3}$$

where

$$k(h) = \begin{cases} \dfrac{1}{\sqrt{2}}, & \text{for } h = 0 \\ (-1)^h, & \text{for } h = 1, \cdots, N-1 \end{cases}$$

the values x_j are given by (2) and $\tilde{T}_h(x)$ is the hth degree normalized Chebyshev polynomial

$$\tilde{T}_0(x) = \frac{1}{\sqrt{2}}; \quad \tilde{T}_h(x) = T_h(x) = \cos(h \arccos x);$$
$$h = 1, \cdots, N-1. \tag{4}$$

In (3), h is the row index and j is the column index.

Denote by $\boldsymbol{g}_N = (g(t_j))_{j=0}^{N-1}$ the vector of nonuniformly spaced samples according to the Chebyshev sampling grid vector $\boldsymbol{t}_N$. Denote by $\boldsymbol{C}_N = (C_0 C_1 \cdots C_{N-1})^T$ the direct discrete cosine transformation (DDCT) of $\boldsymbol{g}_N$, defined as

$$\boldsymbol{C}_N = \boldsymbol{\psi}_N^{\text{DDCT}} \cdot \boldsymbol{g}_N \tag{5}$$

where

$$\boldsymbol{\psi}_N^{\text{DDCT}} = (\sqrt{2/N})\boldsymbol{\psi}_N^{\text{DCT}}. \tag{6}$$

The inverse discrete cosine transform (IDCT) is expressed by

$$\boldsymbol{g}_N = \boldsymbol{\psi}_N^{\text{IDCT}} \cdot \boldsymbol{C}_N \tag{7}$$

where

$$\boldsymbol{\psi}_N^{\text{IDCT}} = (\boldsymbol{\psi}_N^{\text{DDCT}})^{-1} = \sqrt{\frac{N}{2}}\,(\boldsymbol{\psi}_N^{\text{DCT}})^T. \tag{8}$$

Then:

i) For any $t \in [0, L]$, the optimum reconstruction formula which minimizes the maximum instantaneous modulus error is

$$\hat{g}_N(t) = \sum_{h=0}^{N-1} C_h \tilde{T}_h\left(2\frac{t}{L} - 1\right). \tag{9}$$

ii) If the signal $g(t)$ is assumed to be band limited to W, and having a finite energy

$$E = \int_{-W}^{+W} |G(f)|^2 \, df \tag{10}$$

where $G(f)$ is the Fourier transform of $g(t)$

$$G(f) = \int_{-\infty}^{\infty} g(t) \exp(-i2\pi f t) \, dt, \quad i^2 = -1$$

which satisfies $|G(f)| = 0$, for $|f| > W$, then the maximum interpolation error is

$$\epsilon_N = \max_{t \in [0, L]} |g(t) - \hat{g}_N(t)| = \frac{2\sqrt{EW}}{\sqrt{N + \frac{1}{2}}} \cdot \frac{\left(\frac{\pi r}{4} \cdot N\right)^N}{N!} \tag{11}$$

where r is a coefficient defining the average sampling interval

$$\bar{\tau} = \frac{L}{N} = r \cdot \frac{1}{2W}. \tag{12}$$

iii) In order that interpolation converges ($\lim_{N \to \infty} \epsilon_N = 0$), it is sufficient to have $r < (4/\pi e) \cong 0.468$. It means to choose an average sampling rate 2.135 times faster than the Shannon sampling rate.

Proof: The Chebyshev polynomials of the first kind, $T_h(x) = \cos(h \arccos x)$ $h = 1, \cdots, N$ satisfy the following recurrence relation:

$$\begin{aligned} T_{h+1}(x) &= 2xT_h(x) - T_{h-1}(x), \quad x \in [-1, 1] \\ h &= 1, 2, \cdots, N-1 \end{aligned} \tag{13}$$

where

$$T_0(x) = 1, \quad T_1(x) = x.$$

The orthogonal and normalized Chebyshev polynomials given by (4) fulfill the condition

$$\int_{-1}^{1} \rho(x) \tilde{T}_n(x) \tilde{T}_m(x) \, dx = \delta_{n,m} \tag{14}$$

where

$$\rho(x) = 2/(\pi\sqrt{1 - x^2}); \quad \delta_{n,m} = 0$$
$$\text{for } n \neq m; \quad \delta_{n,n} = 1.$$

Approximate $g(x)$, for $x \in [-1, 1]$, by a finite Chebyshev polynomial series

$$\hat{g}_N(x) = \sum_{h=0}^{N-1} C_h \tilde{T}_h(x). \tag{15}$$

We used the Hermite quadrature formula [4], [7]

$$\int_{-1}^{1} \frac{h(x)}{\sqrt{1 - x^2}} \, dx = \frac{\pi}{N} \sum_{j=0}^{N-1} h(x_j). \tag{16}$$

Relations (14)–(16) lead to

$$C_h = \int_{-1}^{1} \frac{2}{\pi\sqrt{1 - x^2}} g(x) \tilde{T}_h(x) \, dx = \frac{2}{N} \sum_{j=0}^{N-1} \tilde{T}_h(x_j) g(x_j). \tag{17}$$

Ahmed *et al.* [1], [2], proved that the matrix $\boldsymbol{\varphi}_N$ having its general element

$$\phi_{h,j} = \sqrt{\frac{2}{N}} k(h) \cos\left[\frac{(2j+1)h\pi}{2N}\right] = (-1)^h \sqrt{\frac{2}{N}} \tilde{T}_h(x_j) \tag{18}$$

(where $k(0) = 1/\sqrt{2}$, $k(h) = 1$, for $h = 1, \cdots, N-1$) is an orthogonal and normalized matrix. Observe that the general term ψ_{hj} of the matrix $\boldsymbol{\psi}_N^{DCT}$ given by (3), differs by the factor $(-1)^h$ only from the general term ϕ_{hj} of the matrix $\boldsymbol{\varphi}_N$. Hence, it results that $\boldsymbol{\psi}_N^{DCT}$ is also an orthogonal and normalized matrix. For $t \in [0, L]$, we use the changing of variables

$$t = (L/2)(1 + x) \tag{19}$$

and from (15) and (17) obtain relation (9). It is easy to prove that $\hat{g}_N(t_j) = g(t_j)$ and to observe that the finite series Chebyshev polynomial (9) is identical with the Lagrangian polynomial of degree $N - 1$ corresponding to the optimum approximation characterized by the grid t_N given by (1) and (2), which minimizes the maximum absolute instantaneous error.

It is well known that [4]

$$\epsilon_N = \max_{t \in [0, L]} |g(t) - \hat{g}_N(t)| \leq \frac{N^N}{2^{2N-1} \cdot N!} \max_{t \in [0, L]} |g^{(N)}(t)|. \tag{20}$$

Taking into account the bound on $g^{(N)}(t)$ given in [13], we obtain

$$|g^{(N)}(t)| \leq \sqrt{E}\left[\pi(2N + 1)\right]^{-1/2} (2\pi W)^{N + (1/2)} \tag{21}$$

where E is given by relation (10).

Using the notation (12) (where $r = (L/N)/[1/(2W)]$ represents the ratio of the average sampling interval to the classical Shannon interval), we obtain relation (11).

According to Stirling's formula [3]

$$N! \cong N^N e^{-N} \sqrt{2\pi N}\left(1 + \frac{1}{12N}\right). \tag{22}$$

Hence

$$\epsilon_N = \sqrt{\frac{2EW}{\pi}} \cdot \frac{1}{\left(1 + \frac{1}{12N}\right)\sqrt{1 + \frac{1}{2N}}} \cdot \frac{\left(\frac{\pi r e}{4}\right)^N}{N}. \tag{23}$$

In order that $\lim_{N \to \infty} \epsilon_N = 0$, it is sufficient to have $r < (4/\pi e) = 0.468$, i.e., the average sampling rate N/L to be approximately two times faster than the Shannon sampling rate.

Normalized Truncation Error Bound Evaluation for Band-Limited Signals

The normalized instantaneous truncation error bounds obtained for sampling reconstruction by our method as well as by Shannon interpolation are given in Table I. The signal $g(t)$ is assumed to be band-limited to the frequency W, and having a finite energy E (relation (10)), where $N' = L$ (even) is the number of nonuniformly taken samples over the interval $[-L/2, L/2]$, according to the proposed method; for the uniform sampling, assume the number of samples is $N' = L + 1$. We deduce the important advantage of our method over the Shannon interpolation for $r = 2W \leq 0.468$. Note that for our method the error bound is considered on the whole definition interval $[-L/2, L/2]$, while for the Shannon interpolation the error bound is taken on the central zone only.

Numerical Examples

Example: Consider the signal $\{g(t) = e^{-t}, t \in [0, 4]\}$.

Assume $N = 8$.

The Chebyshev sampling grid is

$$t_8 = (0.0384294 \quad 0.3370607 \quad 0.8888595 \quad 1.6098194 \quad 2.3901806 \quad 3.1111405 \quad 3.6629392 \quad 3.9615706)^T.$$

TABLE I
NORMALIZED INSTANTANEOUS ERROR BOUND FOR UNIFORM AND NONUNIFORM SAMPLING RECONSTRUCTION

TYPE OF INTERPOLATION BOUND		L \ r	0.436	0.468	0.500
SHANNON UNIFORM SAMPLING RECONSTRUCTION ERROR BOUND IN THE CENTRAL ZONE $\max_{\lvert t\rvert<\frac{1}{2}} \frac{\lvert g(t)-\hat{g}(t)\rvert}{\sqrt{E}}$ (for a signal, g(t), uniformly sampled at the points t=-L/2, -L/2+1,...,-1, 0,1,...,L/2-1,L/2; the number of samples is N'=L+1; L=even; the sampling interval=1; r=1/(1/2W)=2W)	BALAKRISHNAN-PIPER BOUND	L=16	0.159154	0.159154	0.159154
		L=32	0.112539	0.112539	0.112539
		L=64	0.079577	0.079577	0.079577
	PIPER BOUND	L=16	0.097956	0.103068	0.108390
		L=32	0.048978	0.051534	0.054195
		L=64	0.024489	0.025767	0.027097
	YAO-THOMAS BOUND	L=16	0.059310	0.065145	0.071644
		L=32	0.029650	0.032572	0.035820
		L=64	0.014827	0.016286	0.017911
	BROWN BOUND	L=16	0.114763	0.120751	0.126957
		L=32	0.057381	0.060375	0.063493
		L=64	0.028690	0.030187	0.031746
ERROR BOUND OVER THE INTERVAL [-L/2,L/2] OBTAINED BY THE PROPOSED INTERPOLATION CASCADE OF CHEBYSHEV NONUNIFORM SAMPLING FOLLOWED BY DISCRETE COSINE TRANSFORM $\max_{\lvert t\rvert<\frac{L}{2}} \frac{\lvert g(t)-\hat{g}(t)\rvert}{\sqrt{E}}$ (for a signal g(t) nonuniformly sampled in N'=L points over the interval [-L/2,L/2]; the average sampling interval $\bar{\sigma}$=L/N=1; r= $\bar{\sigma}$/(1/2W) = 2W; the convengence condition is: r < 0.468)		L=16	0.007395	0.023796	0.084072
		L=32	0.001174	0.011737	0.070860
		L=64	0.000059	0.005710	0.100716

($g: [-L/2, L/2] \rightarrow \mathcal{R}$, $G(f) = \int_{-\infty}^{\infty} g(t) \exp(-i \cdot 2\pi f t)\, dt$, $i^2 = -1$, $E = \int_{-W}^{W} \lvert G(f)\rvert^2\, df$)

The vector of Chebyshev nonuniformly spaced samples is

$$g_8 = (0.9622996 \quad 0.7138654 \quad 0.4111243 \quad 0.1999237 \quad 0.0916131 \quad 0.0445501 \quad 0.1256569 \quad 0.0190331)^T.$$

The DDCT of g_8 is

$$C_8 = \psi_8^{\text{DDCT}} \cdot g_8 = \sqrt{\tfrac{8}{2}}\, \psi_8^{\text{DCT}} \cdot g_8 = (0.4362965 \quad -0.4305386 \quad 0.186478 \quad -0.0575823 \quad 0.0137306 \quad -2.65935 \cdot 10^{-3} \quad 4.32901 \cdot 10^{-4} \quad -5.995 \cdot 10^{-5})^T.$$

The interpolation formula (9), using the expressions of Chebyshev polynomials given by (4) and (13), leads to

$$\hat{g}_8(t) = \sum_{k=0}^{7} C_k \tilde{T}_k[2t/4 - 1] = 0.9999899 - 0.9996933t + 0.498378t^2 - 0.1633072t^3 + 0.381451t^4 - 6.23515 \cdot 10^{-3}t^5 + 6.361 \cdot 10^{-4}t^6 - 2.9975 \cdot 10^{-5}t^7.$$

A. Interpolation Performance Evaluation

We further evaluate by computer simulation the following interpolation performances:

i) The maximum modulus of the instantaneous error

$$\epsilon_N = \max_{t\in[0,L]} \left| g(t) - \hat{g}_N(t) \right|.$$

ii) The root mean squared interpolation error (continuous variant)

$$(\epsilon_{\text{rms}})_c = \sqrt{\frac{1}{L}\int_0^L \left[g(t) - \hat{g}_N(t)\right]^2 dt}.$$

For the proposed cascade CNS-DCT, the above considered numerical example leads to $(\epsilon_8)_{\text{CNS-DCT}} = 0.932 \cdot 10^{-5}$ and $(\epsilon_{\text{rms}})_{c\text{-CNS-DCT}} = 0.538 \cdot 10^{-5}$.

For comparison, we considered the truncated uniform Shannon interpolation (for the same number of samples $N = 8$). It leads to $(\epsilon_8)_{\text{Shannon}} = 0.579$ and $(\epsilon_{\text{rms}})_{c\text{-Shannon}} = 0.106$. The important advantage of our method over Shannon interpolation is obvious for the considered signal (which is not band limited).

B. Data Compression Performance Evaluation

If we retain only $M = N/2 = 4$ DCT coefficients, the interpolation after compression is given by

$$\hat{g}_{N,M}(t) = \hat{g}_{8,4} = \sum_{k=0}^{M-1} C_k \tilde{T}_k(2t/L - 1) = \sum_{k=0}^{3} C_k \tilde{T}_k(2t/4 - 1) = 0.9831071 - 0.8473456t + 0.2659859t^2 - 0.0287911t^3.$$

iii) To evaluate the fidelity of reconstruction, we define the discrete variant of the root mean-squared reconstruction error

$$(\epsilon_{\text{rms}})_d = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1}\left[g\left(k\frac{L}{N}\right) - \hat{g}_{N,M}\left(k\frac{L}{N}\right)\right]^2}.$$

We obtain $(\epsilon_{\text{rms}})_{d\text{-CNS-DCT}} = 0.0114$.

For comparison, consider the case of the following cascade for the same signal: uniform sampling (US) at the moments $t_k = (kL)/N$, $(k = 0, 1, \cdots, 7)$, the direct discrete cosine transformation (DDCT), compression by retaining the first $M = N/2 = 4$ coefficients and the inverse discrete cosine transform (IDCT) to reconstruct $g(kL/N)$. We obtain $(\epsilon_{\text{rms}})_{d\text{-US-DCT}} = 0.0433$.

The advantage of the cascade CNS-DDCT-compression-interpolation over the classical cascade of US-DDCT-compression-IDCT (for the same average sampling rate) is obvious.

Concluding Remarks

This correspondence provides a method to rapidly compute the coefficients of the optimum interpolation formula starting from the Chebyshev nonuniformly spaced samples of the signal $g(t)$, $t \in [0, L]$, and then applying the DCT. For fast computation of the DCT, there are a lot of available algorithms [5], [9].

In order that interpolation converges, a sufficient theoretical condition is to have an average sampling rate approximately two-times faster than that one required by the Shannon theorem. The advantage of our method over the Shannon interpolation is obvious from Table I (for $r \leq 0.468$).

If we retain only the first M C_k's (DCT coefficients), where $M < N$, relation (9) remains valid, having M instead of N. Thus, we have an efficient formula for signal reconstruction in the case of data compression.

Within a future paper, we intend to present the extension of the proposed cascade CNS-DCT for two-dimensional signals.

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On the Maximum Entropy Method for Interval Covariance Sequences

CRAIG R. SHANKWITZ AND TRYPHON T. GEORGIOU

***Abstract*—Given an interval covariance sequence, we consider the existence of a maximum entropy spectral estimate. It is shown that a maximum entropy spectral estimate does exist, and, moreover, it is unique.**

I. Introduction

Consider a real and scalar stationary zero-mean stochastic process y_t, $t \in \mathbf{Z}_+$. The estimation of the power spectral density of y_t, based on observed samples, usually proceeds in two steps. First, an estimate for the first $n + 1$ covariance lags $c_k = E[y_t y_{t+k}]$, $k = 0, 1, \cdots, n$ is obtained. Second, a spectral density function consistent with the partial covariance sequence $C_n := (c_0, c_1, \cdots, c_n)$ is postulated.

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In the first step errors of a statistical nature are induced on the terms c_k, and the second step involves a nonunique choice among spectra which are consistent with the data. To resolve the nonuniqueness in the second step, and to obtain a "canonical" spectrum, the maximum entropy principle is usually invoked. This requires a spectral estimate that is consistent with the available data and is maximally noncommittal with respect to the unavailable data (see Burg [4] and Jaynes [6]).

To address the issue of the uncertainty associated with the first step, several different formulations have been proposed. For instance, in the work by Schott and McClellan [12], a covariance estimate contaminated by noise is being considered. In that work, the covariance matching constraint of the maximum entropy method is replaced by a weighted inequality, where the weight is based on knowledge of the corrupting noise. Lang and Marzetta [8], [9] use linear programming to provide an upper and lower bound of the power spectral estimate. The inverse Fourier transform relating the covariance at lag k, c_k, to the spectral density function provides the constraints. The approach also provides bounds in the case of "fuzzy" covariance estimates.

In this correspondence, we consider a partial interval covariance sequence defined as follows:

$$\begin{aligned}\mathcal{C}_n := \Big\{ &(c_0, c_1, \cdots, c_n) : c_0 = 1,\\ &c_1 \in [c_{1l}, c_{1u}],\ c_2 \in [c_{2l}, c_{2u}], \cdots, c_n \in [c_{nl}, c_{nu}],\\ &\text{and such that } (c_0, c_1, \cdots, c_n)\\ &\text{is an admissible covariance sequence.} \Big\}\end{aligned}$$

This is a set of possible partial covariance sequences. Any sequence $C_n \in \mathcal{C}_n$ has a unique covariance extension c_k, $k = n + 1, \cdots$, which maximizes the entropy integral

$$H = \int_{-\pi}^{\pi} \log f(\theta)\, d\theta$$

where

$$c_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{-ki\theta}\, d\sigma(\theta), \qquad k = 0, \pm 1, \pm 2, \cdots,$$

and $f(\theta) = \sigma'(\theta)$ a.e. is the respective spectral density function. This is the maximum entropy extension of C_n and the respective extremal value of the entropy integral we denote by $H_{ME}(C_n)$. In this paper we show that there exists a unique element $C_n \in \mathcal{C}_n$ maximizing $H_{ME}(C_n)$ over all $C_n \in \mathcal{C}_n$.

II. Notation and Preliminaries

The set of square matrices of dimension n with real elements is denoted by M_n. The determinant of a matrix M is denoted det (M) and the determinant of M with the ith row and ith column deleted is denoted det $(M(i|i))$.

Consider a sequence $C_n = (c_0, c_1, \cdots, c_n)$, $c_i \in \mathbf{R}$, for $i = 0, 1, \cdots, n$, and the associated Toeplitz matrix

$$\mathbf{T}_{C_n} := [c_{m-k}]_{k,m=0}^{n}$$

where $c_{-n} = c_n$. The sequence C_n is said to be positive (respectively, nonnegative) if $\mathbf{T}_{C_n}$ is positive definite (respectively, positive semidefinite). For a stationary zero-mean stochastic process y_t, $t \in \mathbf{Z}_+$, the covariance sequence $(c_0, c_1, \cdots, c_n)$, $c_i = E[y_t y_{t+i}]$, $i = 0, 1, \cdots, n$ is nonnegative. Conversely, C_n qualifies as a partial covariance sequence of a stationary zero-mean stochastic process if it is nonnegative. Without a loss of generality, we normalize the sequence C_n so that $c_0 = 1$.

Define $\mathcal{P}_n := \{C_n : \mathbf{T}_{C_n} \geq 0\}$. This set is bounded and convex in the Euclidian space $\mathbf{R}^n$. A partial interval covariance sequence

Inversion of the Van der Monde Matrix

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***Abstract*— In this letter we deduce an analytical formula for inversion of a complex Van der Monde matrix. It has applications in signal reconstruction, spectral estimation, system identification, as well as in other important signal processing problems. Since till now the inversion of such a matrix has been performed by approximations, we further deduce an exact inversion formula.**

I. Introduction

There have been several approaches to define a *nonuniform discrete Fourier transform (NDFT)*, the most recent ones belonging to Neagoe [3], [4], [5] and Mitra *et al.* [2]; the definition of the NDFT requires the inversion of a complex Van der Monde matrix. Signal reconstruction [3], system identification and other important signal processing problems necessitate also such inversion. Till now, the inversion of the Van der Monde matrix has been performed by approximations. We further deduce an exact formula for inversion.

II. Preliminary Notations

Consider a Van der Monde matrix of order n over $\boldsymbol{C}$

$$\boldsymbol{A} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ a_1 & a_2 & \cdots & a_n \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ a_1^{n-1} & a_2^{n-1} & \cdots & a_n^{n-1} \end{bmatrix}, \qquad a_k \in C. \tag{1}$$

Denote by

$$\det A = V_n(a_1, \cdots, a_n). \tag{2}$$

We know that

$$V_n(a_1, \cdots, a_n) = \prod_{n \geq i > j \geq 1} (a_i - a_j). \tag{3}$$

For $1 \leq k \leq n-1$, consider the determinant

$$V_n^k(a_1, \cdots, a_n) = \begin{vmatrix} 1 & 1 & \cdots & 1 \\ a_1 & a_2 & \cdots & a_n \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ a_1^{k-1} & a_2^{k-1} & \cdots & a_n^{k-1} \\ a_1^{k+1} & a_2^{k+1} & \cdots & a_n^{k+1} \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ a_1^n & a_2^n & \cdots & a_n^n \end{vmatrix}. \tag{4}$$

For $k = 0$, we define

$$V_n^0(a_1, \cdots, a_n) = \begin{vmatrix} a_1 & a_2 & \cdots & a_n \\ a_1^2 & a_2^2 & \cdots & a_n^2 \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ a_1^n & a_2^n & \cdots & a_n^n \end{vmatrix} \tag{5}$$

and for $k = n$, we also define

$$V_n^n(a_1, \cdots, a_n) = \begin{vmatrix} 1 & 1 & \cdots & 1 \\ a_1 & a_2 & \cdots & a_n \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ a_1^{n-1} & a_2^{n-1} & \cdots & a_n^{n-1} \end{vmatrix}. \tag{6}$$

Obviously

$$V_n^n(a_1, \cdots, a_n) = V_n(a_1, \cdots, a_n). \tag{7}$$

III. Deduction of the Inversion Formula

Consider the Van der Monde determinant of order $(n+1)$, i.e.

$$V_{n+1}(a_1, \cdots, a_n, z) = \begin{vmatrix} 1 & 1 & \cdots & 1 & 1 \\ a_1 & a_2 & \cdots & a_n & z \\ a_1^2 & a_2^2 & \cdots & a_n^2 & z^2 \\ \cdot & \cdot & \cdots & \cdot & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdot \\ a_1^n & a_2^n & \cdots & a_n^n & z^n \end{vmatrix} \tag{8}$$

where z is a complex variable.

We can easily prove that

$$\begin{aligned} &V_{n+1}(a_1, a_2, \cdots, a_n, z) \\ &\qquad = V_n(a_1, a_2, \cdots, a_n) \cdot \prod_{i=1}^{n} (z - a_i). \end{aligned} \tag{9}$$

On the other side, if we develop $V_{n+1}(a_1, a_2, \cdots, a_n, z)$ after its last column, we yield

$$\begin{aligned} V_{n+1}(a_1, a_2, \cdots, a_n, z) &= V_n^n(a_1, a_2, \cdots, a_n.)z^n \\ &- V_n^{n-1}(a_1, a_2, \cdots, a_n)z^{n-1} \\ &+ \cdots + (-1)^n V_n^0(a_1, a_2, \cdots, a_n). \end{aligned} \tag{10}$$

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$$A^{-1} = \left((-1)^{i+j} \frac{\sigma_{n-i}(a_1, \cdots, a_{j-1}, a_{j+1}, \cdots, a_n)}{\prod_{k=1}^{j-1}(a_j - a_k)\prod_{k=j+1}^{n}(a_k - a_j)} \right)^T_{i=1,\cdots,n;\, j=1,\cdots,n} \tag{17}$$

$$A^{-1} = \begin{pmatrix} \frac{\sigma_{n-1}(a_2, a_3, \cdots, a_n)}{\prod_{k=2}^{n}(a_k - a_1)} & -\frac{\sigma_{n-2}(a_2, a_3, \cdots, a_n)}{\prod_{k=2}^{n}(a_k - a_1)} & \cdots & (-1)^{n+1}\frac{1}{\prod_{k=2}^{n}(a_k - a_1)} \\ -\frac{\sigma_{n-1}(a_1, a_3, \cdots, a_n)}{(a_2 - a_1)\prod_{k=3}^{n}(a_k - a_2)} & \frac{\sigma_{n-2}(a_1, a_3, \cdots, a_n)}{(a_2 - a_1)\prod_{k=3}^{n}(a_k - a_2)} & \cdots & (-1)^{n+2}\frac{1}{(a_2 - a_1)\prod_{k=3}^{n}(a_k - a_2)} \\ \vdots & \vdots & \cdots & \vdots \\ (-1)^{n+1}\frac{\sigma_{n-1}(a_1, a_2, \cdots, a_{n-1})}{\prod_{k=1}^{n-1}(a_n - a_k)} & (-1)^{n+2}\frac{\sigma_{n-2}(a_1, a_2, \cdots, a_{n-1})}{\prod_{k=1}^{n-1}(a_n - a_k)} & \cdots & \frac{1}{\prod_{k=1}^{n-1}(a_n - a_k)} \end{pmatrix} \tag{18}$$

Consider the symmetrical polynomials of degree k, $0 \le k \le n$, having as variables $a_1, a_2, \cdots, a_n$, namely

$$\begin{cases} \sigma_0(a_1, a_2, \cdots, a_n) = 1 \\ \sigma_1(a_1, a_2, \cdots, a_n) = a_1 + a_2 + \cdots + a_n \\ \sigma_2(a_1, a_2, \cdots, a_n) = a_1a_2 + a_1a_3 + \cdots + a_1a_n \\ \qquad + a_2a_3 + \cdots + a_2a_n + \cdots + a_{n-1}a_n \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \sigma_n(a_1, a_2, \cdots, a_n) = a_1a_2\cdots a_n. \end{cases} \tag{11}$$

Taking into account that

$$\prod_{i=1}^{n}(z - a_i) = \sigma_0(a_1, a_2, \cdots, a_n)z^n - \sigma_1(a_1, a_2, \cdots, a_n) \cdot z^{n-1} + \cdots + (-1)^n\sigma_n(a_1, a_2, \cdots, a_n) \tag{12}$$

relations (9)–(12) lead to

$$V_n^k(a_1, a_2, \cdots, a_n) = V_n(a_1, a_2, \cdots, a_n)\sigma_{n-k}(a_1, a_2, \cdots, a_n), \quad 0 \le k \le n. \tag{13}$$

Denote by A_{ij} the algebraic complement of the element a_j^{i-1} placed on the ith row and jth column of the Van der Monde matrix $\boldsymbol{A}$, $(1 \le j \le n,\ 1 \le i \le n)$. We have

$$A_{ij} = (-1)^{i+j}\begin{vmatrix} 1 & 1 & \cdots & 1 & \cdots & 1 \\ a_1 & a_2 & \cdots & a_j & \cdots & a_n \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ a_1^{i-1} & a_2^{i-1} & \cdots & a_j^{i-1} & \cdots & a_n^{i-1} \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot & \cdots & \cdot \\ a_1^{n-1} & a_2^{n-1} & \cdots & a_j^{n-1} & \cdots & a_n^{n-1} \end{vmatrix} = (-1)^{i+j}V_{n-1}^{i-1}(a_1, \cdots, a_{j-1}, a_{j+1}, \cdots, a_n). \tag{14}$$

Taking into account relation (13), we obtain

$$A_{ij} = (-1)^{i+j}V_{n-1}(a_1, \cdots, a_{j-1}, a_{j+1}, \cdots, a_n) \cdot \sigma_{n-i}(a_1, \cdots, a_{j-1}, a_{j+1}, \cdots, a_n). \tag{15}$$

It leads to

$$\frac{A_{ij}}{V_n(a_1, a_2, \cdots, a_n)} = (-1)^{i+j}\frac{\sigma_{n-i}(a_1, \cdots, a_{j-1}, a_{j+1}, \cdots, a_n)}{\prod_{k=1}^{j-1}(a_j - a_k)\prod_{k=j+1}^{n}(a_k - a_j)}. \tag{16}$$

Since then, the inverse matrix is expressed in (17), shown at the top of the page, where T denotes the transposition.

It can be equivalently expressed in (18), which appears at the top of the page.

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A Neural Approach to Compression of Hyperspectral Remote Sensing Imagery

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Abstract. This paper presents an original research for hyperspectral satellite image compression using a fully neural system with the following processing stages: (1) a Hebbian network performing the principal component selection; (2) a system of "k" circular self-organizing maps for vector quantization of the previously extracted components. The software implementation of the above system has been trained and tested for a hyperspectral image segment of type AVIRIS with 16 bits/pixel/band (b/p/b). One obtains the peak-signal-to-quantization noise ratio of about 50 dB, for a bit rate of 0.07 b/p/b (a compression ratio of 228:1). We also extend the previous model for removal of the spectral redundancy (between the R, G, B channels) of color images as a particular case of multispectral image compression; we consider both the case of color still images and that of color image sequences.

1 Introduction

Over the next decade the volume of image data generated by airborne and spaceborne *remote sensing* missions will increase dramatically due to the commissioning and launching of sensors with high spatial and spectral resolution. The economics of transmission or storage of these *hyperspectral images* dictates that data *compression* is essential. A hyperspectral image comprises a number of bands, each of which represents the intensity of return from an image scene that is received by a sensor at a particular wavelength.

Hyperspectral imagery provides more information than multispectral imagery in the sense that the spectral resolution of the former is much better than that of the latter. While a multispectral image (for example, LANDSAT), generally requires only five to seven bands, a hyperspectral image of type *AVIRIS* (Airborne Visible/Infrared Imaging Spectrometer) [1], [17] simultaneously acquires *224 channels* (bands) of data in the range of 0.4 to 2.45 μm with an average spectral resolution of 10 nm. Channels of AVIRIS image are originally recorded with 12-bit resolution (compared with typically 8 bits for video) but, after radiometric correction, data is stored as 16-bit words. A property of fine-spectral-resolution imagery is interband correlation. The
3-d correlation (two intraband (spatial) correlations as well as the third interband correlation) facilitates substantial reduction of the data required for storing and/or transmitting such imagery.

A well-known method for image compression is to extract the main directions of the input data set; this is equivalent to the computation of the Karhunen-Loeve Transform (KLT) [14]. The corresponding KLT matrix is obtained by computing the eigenvectors of the autocorrelation matrix of the input data. This problem is also called "Principal Component Analysis" PCA).

We have chosen *a neural solution of the PCA* by maximizing the information contained at the outputs of a special neural network called "Hebbian" [5], [14], [16]. If we use a specific training rule called Sanger rule [5], [14], [18], then we can prove that the weight vectors do not depend on the initial conditions and they will always converge to the eigenvectors of the autocorrelation matrix of the input data. Since then, *the Hebbian net may be considered as a neural equivalent of the KLT.*

Another common image compression method is *vector quantization*, which can achieve high compression ratios [9]. A vector quantizer makes use of the fact that a large number of possible blocks in an image look similar. These blocks are mapped to a single block (called *prototype* of the corresponding class), which is given a code that has fewer bits than the actual block representation. The image compression problem then becomes the task of finding the block in the codebook, which most closely represents an original block (namely, finding the *nearest prototype*).

Some advanced techniques for *vector quantization* belong to the field of *computational intelligence* using *neural* models. *Neural vector quantization* of images [11], [12], [13], [15] is based especially on the Kohonen Self-Organizing Map (SOM) [7]. Neighboring neurons in the above-unsupervised neural network develop adaptively into specific detectors of different vector patterns. The neurons become specifically tuned to various classes of patterns through a competitive, unsupervised or self-organizing learning. Only one cell (neuron) or group of cells at a time gives the active response to the current input. The spatial location of a cell in the network (given by its co-ordinates) corresponds to a particular input vector pattern.

First contribution of the present paper is the design, software implementation and evaluation of a fully neural model for compression of hyperspectral satellite imagery (instead of the conventional (non-neural) methods used in [1]). Our model consists of a Hebbian network (for principal component selection, that extracts the 3-d correlation of the hyperspectral image data) cascaded by a set of Kohonen network (for neural vector quantization). *The second contribution of the paper is to extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B principal components*. For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes three. For representation of color image sequences, the model includes a first processing stage consisting of a 4-dimensional orthogonal transform (instead of the 3-d transform used for hyperspectral imagery) for extraction of the principal component of the input color image sequence followed by a second processing stage of *neural* vector quantization. The experimental compression results are given both for the principal model (compression of hyperspectral satellite imagery) as well as for the special application (compression of color images).

2 A Fully Neural Model for Compression of Hyperspectral Imagery

2.1 Model Description

The proposed model (Fig. 1) contains the following processing cascade:

(a) The Hebbian network for *extraction of the principal components*;

(b) A set of self-organizing neural networks (Kohonen) for *vector quantization* of the principal components.

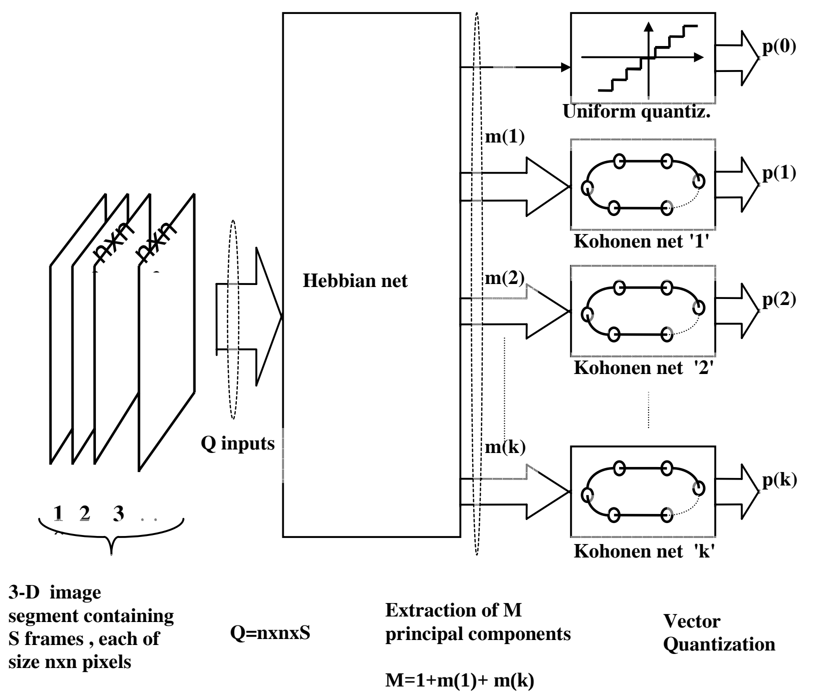


Fig. 1. Architecture of the neural system for compression of hyperspectral imagery.

(a) *The Hebbian network* processes the 3-d elementary blocks of "n x n x S" pixels of the input hyperspectral sequence (where “n x n” is the elementary analysis square in each “N x N” pixel band, and S is the number of bands. This network is a neural replica of the optimum 3-d Karhunen-Loeve transform.

To improve the convergence, we have chosen the initial weights of the network to be given by the elements of the matrix defining the 3-d Discrete Cosine Transform (3-d DCT). The network has Q=n x n x S inputs, corresponding to the above-mentioned 3-d multispectral segment and M outputs, corresponding to the principal components. The neural variant has the advantage (over the non-neural one=KLT) of deducing the optimum transformation by a simple and iterative technique instead of requiring a significant computational effort for evaluating the autocorrelation matrix, the eigenvalues and eigenvectors!

(b) *The system of "k" circular self-organizing map*s performs vector quantization of the M-1 (AC) principal components, given by the Hebbian network. These components are grouped into "k" subsets, so that m (1) + m (2)+…+m (k)= M-1, where m (h) is the number of inputs of the self-organizing map of index "h"; each network has 2exp[p (h)] neurons (outputs), where p (h) is the number of bits for encoding the segment "h" of the principal component set. First component is uniformly quantized with p (0) bits. Since then, the bit rate provided by the neural compression system is R = p (0)+p (1)+…+p (k)]/(n x n x S) bits/pixel/band (b/p/b).
The radius of the neighborhood of each neuron decreases with the iteration. The *circular* architecture of the network implies a perfect symmetry.

2.2 Experimental Results for Compression of Hyperspectral Imagery

We have used hyperspectral images of the type AVIRIS (Airborne Visible/Infrared Imaging Spectrometer). The images are selected from a hypercube containing 128 spectral bands, each band with 128 **x** 128 pixels. The images are represented with a radiometric resolution of 16 bits/pixel/band and correspond to an urban area.

2.2.1 Training

a. Selection of the principal components (Hebbian Network)

- We have used S=8 spectral bands (avir_1.raw,….., avir_8.raw)
- The size of each band: N x N= 128 x 128 pixels
- Resolution: 16 bits/pixel
- The input multispectral image is segmented into 3-D blocks of 8 x 8 x 8 (namely, n=S=8)
- Number of inputs of the Hebbian network: n x n x S=512
- Number of outputs (selected components): M= 20

The training of the Hebbian network may be evaluated in Table 1.

b. Quantization of the Principal Components (Neural Self-Organizing System)
- The DC coefficient is scalar quantized with p (0)=9 bits.
- The set of M-1 = 19 AC coefficients are vectorially quantized by segmenting the set into k = 3 subsets of sizes: m (1)=7; m (2)=6; m (3)=6.

• Each of the three neural networks has a circular architecture with 512 neurons (it implies that a corresponding prototype is encoded with p (1)=p (2)=p (3)= 9 bits).
• The resulted bit rate is R= (9+27)/512= 0.07 bits/pixel/band (b/p/b), corresponding to the compression factor of F=16/0.07=228:1.
• The objective quality of the reconstructed bands of the hyperspectral training image after processing by the Hebbian network, *with* and *without* neural quantization may be evaluated from the Table 2.

Table 1. Peak signal-to-quantization noise ratios during the refinement of the Hebbian network for the hyperspectral image AVIRIS (8 bands: avir_1.raw, avir_2.raw,…,avir_8.raw); number of retained coefficients: M=20 (t= index of epoch)

t (epoch)	0	1	2	3	4	Frozen after t=4
(PSNR) dB (Global)	49.56	49.65	49.77	49.84	49.87	49.87
(PSNR) dB (Band1)	48.41	48.79	49.53	50.10	50.52	50.73
(PSNR) dB (Band 2)	51.37	51.35	51.31	51.21	51.07	51.01
(PSNR) dB (Band 3)	51.06	51.00	50.87	50.75	50.65	50.59
(PSNR) dB (Band 4)	48.72	48.80	48.94	49.05	49.16	49.20
(PSNR) dB (Band 5)	50.04	50.11	50.23	50.33	50.41	50.45
PSNR) dB (Band 6)	50.76	50.78	50.84	50.86	50.86	50.87
(PSNR) dB (Band 7)	51.05	51.21	51.43	51.53	51.55	51.54
(PSNR) dB (Band 8)	47.11	47.10	47.00	46.91	46.83	46.76

Table 2. Peak signal-to-quantization noise ratios of the hyperspectral *trainin*g sequence AVIRIS (8 bands: avir_1.raw,…,avir_8.raw) processed firstly by the Hebbian network (after freezing the weights obtained during 4 epochs of training and retaining M=20 components) and then reconstructed *without* or *with* neural quantization

	Global	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8
(PSNR) dB Reconstruc-tion **without** quantization	49.87	50.73	51.01	50.59	49.20	50.45	50.87	51.54	46.76
(PSNR) dB Reconstruc-tion **with.** quantization	49.69	50.53	50.79	50.39	49.05	50.25	50.65	51.28	46.64

•We can remark a high fidelity of the quantization (the global signal-to-quantization noise ratio decreases only from 49.87 dB to 49.69 dB as effect of quantization!).

• In Fig. 2 (a, b, c), we can subjectively evaluate the quality of the reconstructed image corresponding to Table 2 (band 3 of the considered training image). Visually, we cannot remark any difference between the input and the reconstructed image.

(a)

(b)

(c)

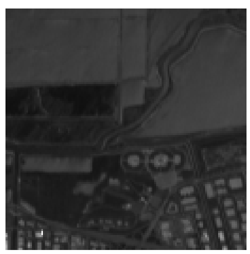
Fig. 2. **(a)** Original band 3 (avir_3.raw). **(b)** Band 3 reconstructed after Hebbian selection of the principal components without quantization (PSNR=50.59 dB). **(c)** Band 3 reconstructed after Hebbian selection of the principal components and vector quantization with a system of three self-organizing neural networks (PSNR=50.39 dB, R= 0.07 b/p/b; compression ratio=228:1).

2.2.2 Testing

• We have used the set of eight bands of the hyperspectral image (avir_9.raw,…,avir_16.raw), different from those used for training, but corresponding to the same urban area.
• The parameters of the input sequence, those of the Hebbian network, as well as those of the Kohonen system are the same as for the training phase.
• In Table 3, we can evaluate the objective quality of the reconstructed picture (peak signal-to-quantization-noise ratio =PSNR) for the hyperspectral test image, while in Fig. 3 (a, b, c) we can visually evaluate the reconstructed test picture (band 10). *The signal-to-noise ratio (**about 50 dB!**) and the high compression ratio (of **228:1**) combine the high quality of reconstruction with an important coding efficiency.*

Table 3. Peak signal-to-quantization noise ratios of the hyperspectral *test* sequence AVIRIS (8 bands: avir_9.raw,…,avir_16.raw) processed firstly by the Hebbian network, and then reconstructed *without* or *with* neural vector quantization (after freezing the weights obtained during 4 epochs of training and retaining M=20 components). The neural system has been trained on the multispectral sequence of 8 bands: avir_1.raw,…,avir_8.raw.

	Global	Band 9	Band 10	Band 11	Band 12	Band 13	Band 14	Band 15	Band 16
(PSNR) dB Reconstruction **without** quantization	**49.10**	46.16	50.46	50.15	48.62	49.57	50.73	50.33	48.83
(PSNR) dB Reconstruction **with** quantization	**47.95**	45.40	48.87	48.83	47.69	48.41	49.18	48.60	47.93



(a)

(b)

(c)

Fig. 3. (a) Band 10 original (avir_10.raw; 128 x 128 pixels). **(b)** Band 10 reconstructed after Hebbian selection of the principal components without quantization (PSNR=50.46 dB). **(c)** Band 10 reconstructed after Hebbian selection of the principal components and vector quantization with a system of 3 self-organizing neural networks (PSNR=48.87dB, R= 0.07 b/p/b; compression ratio=228:1). The neural system (Hebbian + Kohonen) has been trained on the multispectral sequence of 8 bands: avir_1.raw,…, avir_8.raw.

3 Removal of the Spectral Redundancy of Color Images as a Particular Case of Multispectral Image Compression

3.1 Compression of Still Color Images

We further extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B component images! For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes 3. Thus, *we build an original model for color image representation,* by considering in the same 3-d orthogonal transformation not only the 2-d spatial correlation ***but also the spectral correlation between the R, G, and B components***! One can approximate the Hebbian network by a suboptimum 3-d orthogonal transform like 3-d Discrete Cosine Transform (3-d DCT) with a small reduction of data compression performances but with a significant increasing of the computation speed.

Experimental Results

We have trained and tested this special application for the color picture "Girl" of 512 x 512 pixels, represented in true-color bmp (24 bits/pixel).

General parameters

• The 3-d segment has the sizes: $n_1 = n_2 = 8$, S =3, corresponding to the hyper-rectangle of 8 x 8 x 3.

• Number of retained coefficients (principal components) after 3-d DCT processing: M=25

• The first 3-d DCT coefficient (0,0,0) has been scalar quantized with p (0) = 8 bits.

Parameters of the neural system

• The set of M-1 = 24 AC coefficients are vectorially quantized by segmenting the set into k= 3 subsets of sizes: m (1)= m (2)= m (3)=8, each subset containing the inputs of a corresponding circular self-organizing map for vector quantization.

• Size of each ring network: 256 x 1 (p (1) = …. =p (3)= 8 bits)

• The resulted bit rate is R= (8+24)/(8 x 8 x 3) = 0.167 bits/pixel/channel (b/p/c), or, for other representation is R= (8+24)/(8 x 8)=0.5 bits/true-color pixel. It corresponds to the compression factor of F=24/0.5=48:1.

Table 4. Signal-to-quantization noise ratios for each color channel of the reconstructed color image "Girl" after 3-d DCT and neural vector quantization

(PSNR) red [dB]	(PSNR) green [dB]	(PSNR) blue [dB]
25.02	22.37	26.60

The *objective quality of the reconstructed "Girl" is given in Table 4 and the subjective* quality of the reconstructed color image after compression may be evaluated from Fig. 4.

(a)

(b)

Fig. 4. (a) Original "Girl". **(b)** Reconstruction of the "Girl" after 3-d DCT and neural quantization (compression ratio R=48:1).

3.2 Compression of Color Image Sequences

We extend for color image sequences the previous model of compression of hyperspectral images. Instead of separately processing the color image sequences (for each of the fundamental colors R, G, B), we have chosen a global processing for redundancy removal taking into account in the same processing stage the 4-d correlation of the color image sequences: two dimensions of spatial correlation, one dimension for temporal correlation *and also one dimension for spectral correlation (corresponding to the R, G, B bands!). We choose a 4-dimensional orthogonal transform for color sequence representation,* instead of the well-known 3-d transform or hybrid coding (2-d transforms combined with prediction) for each color components. Thus, we consider in the same orthogonal transformation not only the spatial correlation and the temporal one*, but also the spectral correlation between the R, G, B channels. For example, we have chosen* a 4-dimensional Discrete Cosine Transform (4-d DCT), that is an approximation of the KLT (Hebbian net) that reduces the computational complexity. The 4-d DCT coefficients are given by the relation

$$C(k_1,k_2,k_3,k_4)=\frac{u(k_1)\cdot u(k_2)\cdot u(k_3)\cdot u(k_4)}{\sqrt{N_1N_2N_3N_4}}\cdot$$

$$\left(\sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1}\sum_{n_3=0}^{N_3-1}\sum_{n_4=0}^{N_4-1} x(n_1,n_2,n_3,n_4)\cos\frac{\pi(2n_1+1)k_1}{2N_1}\cos\frac{\pi(2n_2+1)k_2}{2N_2}\cos\frac{\pi(2n_3+1)k_3}{2N_3}\cos\frac{\pi(2n_4+1)k_4}{2N_4}\right)$$

where $u(k_i)=\begin{cases}1, & k_i=0\\ \sqrt{2}, & k_i=1,\dots,N_i-1\end{cases}$

$i\in 1,2,3,4$, n_i and k_i belong respectively to the sets $\{0,\dots,N_1-1\}$, $\{0,\dots,N_2-1\}$, $\{0,\dots,N_3-1\}$ and $\{0,\dots,N_4-1\}$. Here, $N_1 = N_2 = n$ (elementary analysis square); N_3 is equal to S=frame number; N_4 =3 (number of channels). In the previous relation, we consider that a color image sequence segment expressed in the (R, G, B) format are represented by the corresponding 4-dimensional matrix x (i, j, k, h), for i = 0,…, N_1-1, j = 0,…,N_2-1, k = 0,…,N_3-1 and h = 0,…,N_4-1. The M retained 4-d DCT coefficients corresponding to the principal components of the input color image sequence segment are grouped in several sets (vectors) and each such a vector is applied to a corresponding *neural quantizer* .

Processing stages of the proposed model:

(a) a 4-d orthogonal transform of each input 4-d matrix of "N_1 x N_2 x N_3 x N_4" fundamental color pixels into a set of M selected components in the frequency domain (where N_1 x N_2 are the sizes of the square analysis segment of a certain frame, N_3 is the number of frames considered to be redundant, and a color pixel corresponds to N_4 =3 monochrome pixels, one for each of the fundamental colors R, G, B).

(b) a neural vector quantization system, consisting of "k" vector quantizers of the M-1 selected components (the AC ones) obtained as a result of the previous processing stage, where the selected components are grouped into "k" subsets

Remarks:

- All "k" neural vector quantizers are trained using one or several image sequences.
- After training, we perform the processing of an input sequence according to the previous mentioned stages (a) and (b).

(a)

(b)

Fig. 5. (a) Original first frame of the color sequence "Miss America". **(b)** Reconstruction of the first frame of the color sequence "Miss America" (having 8 frames) using the proposed neural model (trained on the same sequence) (compression ratio R=150:1).

Experimental Results

We have designed and implemented the software of the **neural** system shown in Fig. 1, where instead of the Hebbian network, we have used a 4-d DCT. For experimenting the corresponding system, we have used two image sequences: "Miss America" (misa) and “Salesman”; each experimental sequence had a length of maximum 64 frames of 256 x 256 pixels /frame with 24 bits/true-color pixel.

General parameters

• Number of retained coefficients (principal components): M=270

• The first 4-d DCT coefficient (0,0,0,0) has been scalar quantized with p (0) = 10 bits.

Parameters of the neural system

We have used a system of k=9 circular self-organizing maps (Kohonen networks). Each network has a number of 2exp [p (h)] neurons (outputs), where p (h) is the number of bits to encode the group (“h”) of m (h) principal components. The neural system has the following parameters:

• *First six networks:*

♦ number of inputs: m (1) = …=m (6)=36;

♦ size of the ring networks: 256 x 1 (p (1) = …. =p (6)= 8 bits)

• *Seventh and eight networks:*

♦ number of inputs: m (7) = m (8)=37

♦ size of the ring networks: 256 x 1; (p (7) = p (8)=8 bits)

• *Ninth network*

♦ number of inputs: m (9) = 39

♦ size of the ring network: 256 x 1 (p (9) = 8 bits).

• Resulted bit rate is BR=0.16 bits/true-color pixel (compression ratio R= 150:1)

• The peak signal-to-quantization noise ratios of the reconstructed first frame of the sequence “Miss America” (for the main bands R, G, B) are given in Table 5, while the *subjective* quality of the reconstructed color frame after compression may be evaluated in Fig. 5.

Table 5. Signal-to-quantization noise ratios for each color channel of the reconstructed first frame of the color sequence „Miss America“.

(PSNR) red [dB]	(PSNR) green [dB]	(PSNR) blue [dB]
33.54	34.95	33.14

4 Concluding Remarks

1. This paper *presents a fully neural model for compression of hyperspectral satellite imagery* consisting of a Hebbian network (for principal component selection, that extracts the 3-D correlation of the hyperspectral image data) cascaded with a set of ring Self-Organizing Maps (for neural vector quantization of the previously extracted components).

2. By the proposed neural model, we point out the feasibility of applying an exciting technique of computational intelligence for compression of satellite imagery, instead of the conventional techniques.

3. If we compare the Hebbian network with the KLT, the neural variant has a significant advantage in reducing the computational effort, avoiding the necessity of deducing the autocorrelation matrix, its eigenvalues and eigenvectors and so on. The neural vector quantization proves also to be competitive with the classical (non-neural) vector quantization for the image compression task.

4. We give the experimental results of the software implementation of the previous model for compression of the hyperspectrral images AVIRIS. One obtains very good results: the peak-signal-to-quantization-noise-ratio of about 50 dB for each band, for a bit rate of 0.07 b/p/b (a compression ratio of 228:1). *This means a high quality of image reconstruction combined with a significant coding efficiency.*

5. As a special application, we extend the present model based on interband correlation by considering a color image as a multispectral picture corresponding to the three R, G, B channels. For compression of color still images, the scheme remains the same as for hyperspectral satellite images, but the number of bands becomes 3, corresponding to the R, G, B channels. Thus, *we obtained an original model for color image representation,* by considering in the same 3-d orthogonal transformation not only the 2-d spatial correlation *but also the spectral correlation between the R, G, B components*! To increase the computation speed we replace the Hebbian network by the 3-d DCT.

6. By extending the initial scheme to *the representation of color image sequences*, *we build a new model that includes a 4-dimensional orthogonal transform as a first processing stage* (instead of the 3-d transform for hyperspectral imagery) for extraction of the principal components. Thus, we consider in the same 4-d orthogonal transformation the redundancy removal corresponding to the following four correlation dimensions: the 2-d spatial correlation (the first two dimensions), the temporal one (the third dimension), and the spectral correlation between the R, G, B bands (the fourth dimension)! We have applied this 4-d orthogonal representation model for the particular case of the 4-d DCT, instead of the Hebbian net, to reduce the computational effort. The second processing stage (*neural* vector quantization) remains the same as for compression of hyperspectral images.

7. The very good experimental compression results are obtained both for color still images (compression ratio of 48:1) and also for color image sequences (compression ratio of 150:1).

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An Optimum 2D Color Space for Pattern Recognition

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Abstract - *This paper presents an optimum color conversion from the 3D RGB space into a 2D selected space to the purpose of pattern recognition. The method is based on the Karhunen-Loève transform (KLT), also known as Principal Component Analysis (PCA). The resulted 2D space is defined by the two color components (called C_1 and C_2), corresponding to the two largest eigenvalues of the RGB pixel covariance matrix. Using the above color projection technique, we propose a color face recognition system based on feature fusion of the C_1 and C_2 components and a concurrent neural network classifier. The proposed system is experimented for a color face database containing 3520 color images of 151 subjects. We also present a color image segmentation using pixel clustering in the 2D color space by means of a self-organizing neural network. The new 2D color projection model may have wide applications in the areas of color-based pattern recognition.*

Keywords: *optimum 2D color conversion, color-based pattern recognition, color face recognition, color image segmentation*

1 Introduction

Like humans, the artificial intelligence systems use *color*, shape and texture for pattern recognition. There are a lot of systems for pictorial content representation and recognition based on color features.

Color image segmentation is a significant research area, useful in many applications. From the segmentation results, it is possible to identify regions of interest and objects in the scene, which is very beneficial to the subsequent image analysis.

All about the world, governments and private companies are putting *biometric technology* at the heart of ambitious projects, ranging from access control and company security to high-tech passports, ID cards, driving licenses, and company security. One of most important areas of biometric technology is *face recognition***.** A common feature found in almost all technical approaches proposed for *face recognition* is the use of only the luminance associated to the face image. Although the majority of images are recorded in the color format nowadays, most face recognition systems convert the color information to luminance component data and do no use color information. One of the key challenges in face recognition lies in determining the contribution of different cues to the system performance and one of these cues is the *color* attribute.

We further present an approach to improve the color-based pattern recognition performance by optimizing the color conversion. In [8], a neural model is given, for exploiting both *spectral* and also spatial image correlation, to reduce space dimensionality of color pictures. Recently, Jones and Abbott [1] performed a color conversion of the R, G, B components into the optimized monochrome form (instead of luminance) for face recognition, using the Karhunen-Loève transformation (KLT). We extend their approach by proposing and evaluating the transformation of the 3D RGB space into a 2D optimized space.

Then we propose a color face recognition system, where the images belonging to the face data base were projected in the previously mentioned KLT 2D color space (of components C_1 and C_2). For feature extraction, one chooses the Principal Component Analysis (PCA) model for each of the C_1 and C_2 channels. The next stage corresponds to *feature fusion*. The last processing stage means the application of the multiple neural system called CSOM (Concurrent Self-Organizing Maps) [7]. For comparison, we considered two scheme variants of color face recognition based on the 3D RGB color space. The systems are evaluated using the Essex color face database (151 selected subjects).

The application of the new 2D color projection techniques for color image segmentation is also considered. Using a 2D color optimized representation, proposed in this paper, instead of the 3D color space, one can significantly reduce the computational effort, by preserving the information content.

2 Color Conversion from RGB Space into an Optimum 2D Space for Pattern Recognition

Consider the color pixels in a given image as 3D vectors

$$\mathrm{P(x,y)} = \begin{bmatrix} R(x,y) \\ G(x,y) \\ B(x,y) \end{bmatrix},$$

where R(x, y), G(x, y) and B(x, y) are the red, green and blue components of the pixel of co-ordinates (x, y).

We assume that color images exhibit features that can be useful in the conversion from a 3D full color space representation to the 2D space. For color conversion, we have chosen the Karhunen-Loève transformation (KLT), also known as Principal Component Analysis (PCA), by exploiting the correlation of the R, G, and B color channels. It is an *optimum projection solution*, by minimizing the mean square error for vector dimensionality reduction, when one projects the 3D RGB space into the 2D *KLT color space* with uncorrelated axes.

To deduce the KLT matrix, one firstly computes the covariance matrix of the color pixels (represented as 3D vectors). Then, one computes the eigenvalues of the covariance matrix. Finally, we deduce the two eigenvectors, corresponding to the largest two eigenvalues. Thus, one obtains the KLT matrix K

$$\mathrm{K} = \begin{bmatrix} \mathrm{A}^{\mathrm{T}} \\ \mathrm{B}^{\mathrm{T}} \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{bmatrix},$$

where

$$\mathrm{A} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}, \qquad \text{and } \mathrm{B} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix},$$

(A and B are the eigenvectors of the covariance matrix corresponding to the two largest eigenvalues and T denotes transposition).

Then, the projection of the 3D color vector P(x,y) in the 2D space is the vector C(x,y)

$$\mathrm{C(x,y)} = \begin{bmatrix} C_1(x,y) \\ C_2(x,y) \end{bmatrix},$$

given by the equation

$$\mathrm{C(x,y)} = = \mathrm{K} \bullet \mathrm{P(x,y)}.$$

2.1 Example 1

One assumes the image ("peppers") in Fig. 1 (a), having 256 x 256 pixels with 24 bits/pixel.

The eigenvalues of the covariance matrix are

$$\lambda_1 = 7334.6;\ \lambda_2 = 1803.0\ ;\ \lambda_3 = 347.8.$$

For the above example, by retaining first two largest eigenvalues, one deduces that the projection error is of 3.66% only!

The corresponding eigenvectors defining color KLT are

A^{T} = (0.2490 0.8428 0.4772)
B^{T} = (0.9492 -0.3102 0.0525).

(a) (b)

Fig. 1. (a) Original "peppers". (b) Reconstructed "peppers" from 2D KLT color space.

Thus, one can perform the projection in the 2D space. In Fig. 1(b), the reconstructed version of the image 1(a) from 2D space is given.

2.2 Example 2

We considered the original RGB image in Fig. 2(a) (from Berkeley segmentation data set) and the reconstructed version from its 2D KLT projection (Fig. 2(b)). One can remark that the reconstructed picture is very similar to the original.

(a) (b)

Fig. 2. (a) Original "Berkeley". (b) Reconstructed "Berkeley" from 2D KLT color space.

3 Color Image Segmentation Using 2D Pixel Clustering

We further apply the previous color conversion method for *color image segmentation*. We perform clustering of color pixels represented as 2D vectors (by the corresponding C_1 and C_2 color components).

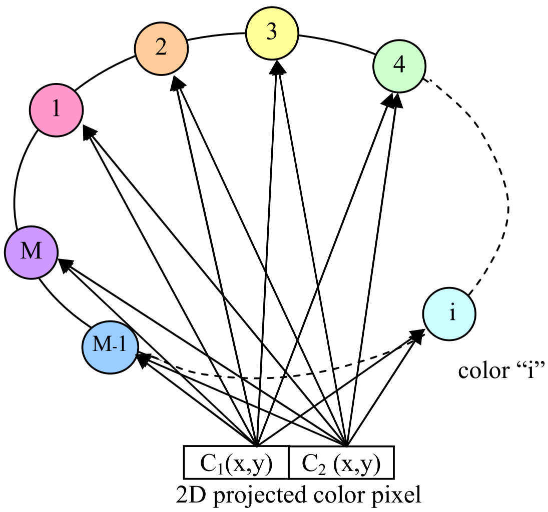

Fig. 3. Circular self-organizing map for color pixel clustering in the 2D KLT color space.

The above vectors are applied to the input of a Self-Organizing Map (SOM), also called Kohonen neural network, having a circular architecture with M output neurons (Fig. 3). Each output neuron is a potential prototype of a color class, so that the maximum number of color classes (M), is given by the number of output neurons. The system stores the correspondences between input pixels (2D vectors) and the index of the corresponding winning neuron, so that we can assigned to each class a *natural* color that is the average of the colors characterizing the pixels assigned to that class. The *pseudo-color* representation can also be used.
We have assumed as input the color image "peppers" given in Fig. 1(a). The result of segmentation (by pixel clustering in the 2D space) is the representation of the considered picture by maximum M color classes (see Fig. 4). The cases of M=10 in Fig. 4(a, c) and M=5 in Fig. 4(b, d) are considered.

For comparison, we experimented the pixel clustering in the 3D RGB space using the same kind of neural network (Fig. 3), but using a 3D input (R, G, B). The results of simulation are given in Fig. 5.

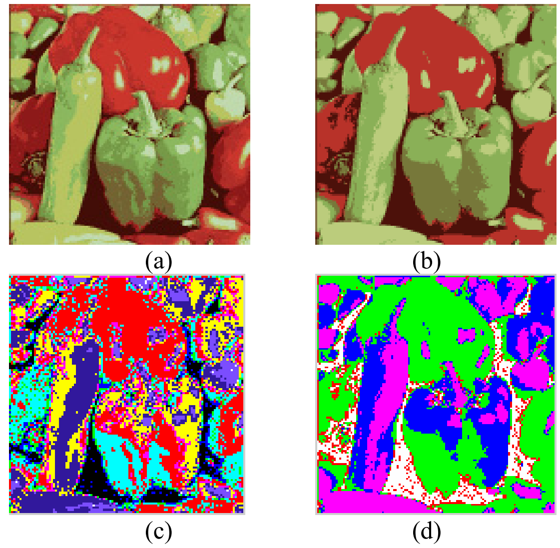

Fig. 4. Segmented "peppers" by 2D pixel clustering in M color classes with a circular SOM. The inputs are 2D vectors of (C_1, C_2) color components. Use M output neurons: (a) natural colors, M=10; (b) natural colors, M=5; (c) pseudo-colors, M=10; (d) pseudo-colors, M=5.

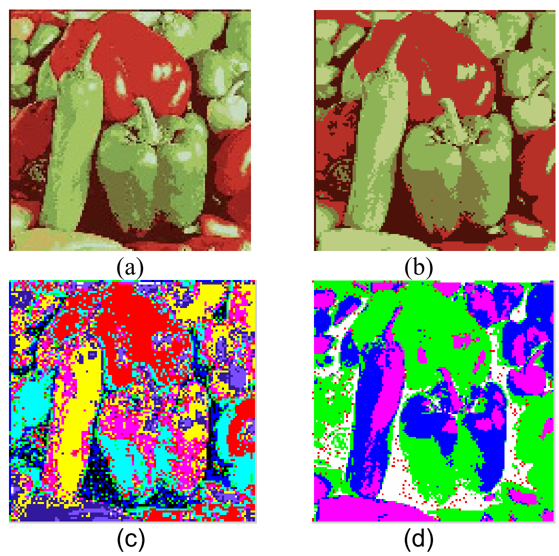

Fig. 5. Segmented "peppers" by 3D pixel clustering in M color classes with a circular SOM. The inputs are 3D vectors of (R, G, B) color components. Use M output neurons: (a) natural colors, M=10; (b) natural colors, M=5; (c) pseudo-colors, M=10; (d) pseudo-colors, M=5.

The advantage of 2D representation over RGB is that by performing a color image segmentation in a space with 2 dimensions (instead of 3), one can obtain an equivalent clustering quality with a reduced computational effort.

4 Face Recognition in the 2D Color Space

4.1 Feature Fusion Model

Using the proposed color projection model, a new system of color face recognition is proposed (Fig. 6). It contains the following processing stages:

1) Color conversion of the R, G, and B components into the two optimized new components C_1 and C_2, according to the KLT
2) Principal Component Analysis (PCA) for each of the two color channels (C_1 and C_2)
3) Feature fusion (amalgamation of the eigen-components of the two channels)
4) Neural network classification. The final processing stage consists of a set of Concurrent Self Organizing Maps (CSOM) [7] shown in Fig. 7.

Concurrent Self-Organizing Maps (CSOM) is a collection of small SOMs, which use a global *winner-takes-all* strategy. Each network is used to correctly classify the patterns of one class only and the number of networks equals the number of classes.

The CSOM training technique is a supervised one, but for any individual net the SOM specific training algorithm is used. We built "n" training patterns sets and we used the SOM training algorithm independently for each of the "n" SOMs. The CSOM models *for training and classification* are shown in Figs. 7 (a) and (b).

For comparison, we further consider two scheme variants of color face recognition, where their inputs are 3D vectors (RGB pixels). In Fig. 8, one can see a model based on the independent processing of the R, G, and B channels. After PCA and neural classification, we can follow one of the color decision or we can perform a decision fusion (for example, by vote). The system in Fig. 9 uses the fusion of the eigen-features corresponding to the R, G, and B color components, followed by the neural classifier.

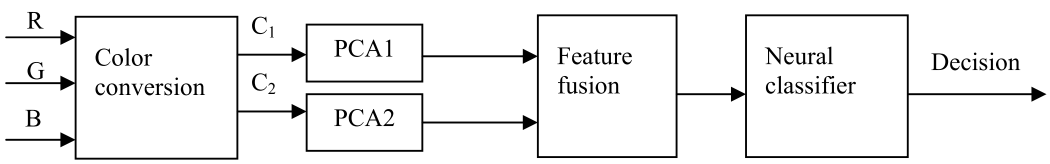

Fig. 6. Color face recognition with color conversion and feature fusion (*using as inputs 2D projected pixels*).

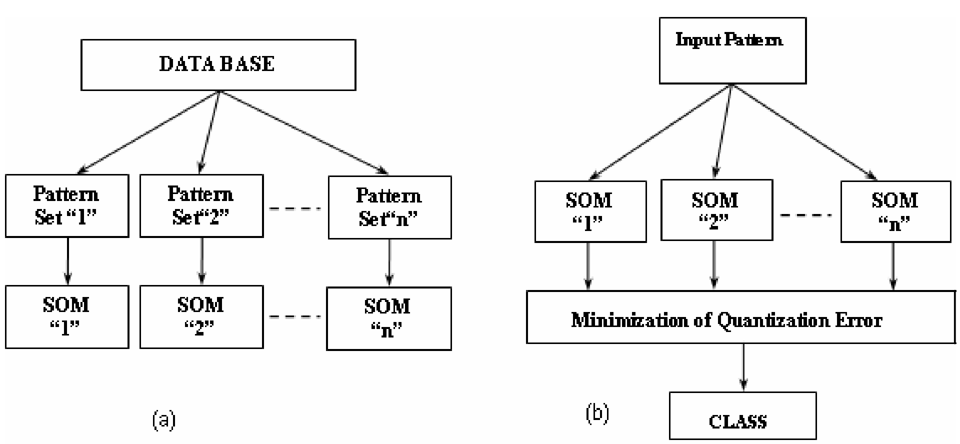

Fig. 7. (a) The CSOM model (training phase). (b) The CSOM model (classification phase).

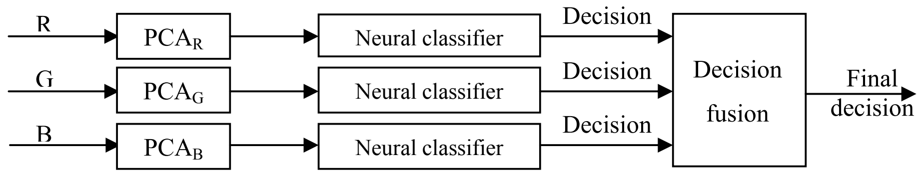

Fig. 8. Color face recognition using the R, G, B components and a decision fusion.

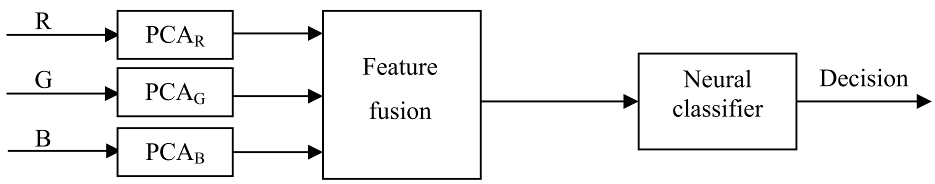

Fig. 9. Color face recognition using feature fusion of the R, G, B channels.

4.2 Experimental Results

We have used the color face database provided by Dr. Libor Spacek, Depart. of Computer Science, University of Essex, U.K. We considered 3020 images from this database, corresponding to 151 subjects, where each subject is represented by 20 pictures (10 images being chosen for training and the other 20 for test). Any picture has 200 x 180 pixels, in RGB format (with 24 bits/pel).

The face database contains images of people of various racial origins, most of them being of 18-20 year old, but some older individuals are also present (Fig. 10).

We have considered both the original images selected from data base and also the corresponding intentionally degraded ones (Fig. 12). The experimental results are given in Tables 1-2 and Figs. 14-17.

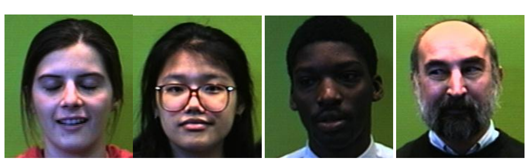

Fig. 10. Several images belonging to the Essex database.

The eigenvalues of the color pixel covariance matrix for the training set of 1510 face images are

$$\lambda_1 = 8140.67;\ \lambda_2 = 984.34\ ;\ \lambda_3 = 223.35.$$

One deduces that the projection error (corresponding to least eigenvalue) is of 2.39% only!

The corresponding eigenvectors defining the color KLT are

$$A^T = (0.6411\ 0.5568\ 0.5282)$$

$$B^T = (0.1273\ -0.7558\ 0.6423).$$

In Fig. 11 (b) one can see the reconstruction of image (11.a) from the 2D KLT color space.

(a) (b) (c) (d)

Fig. 11. (a) Original "Ekavaz". (b) Reconstruction of (a) from 2D KLT color space. (c) Reconstruction of (a) from 1D KLT color space. (d) Luminance component of (a).

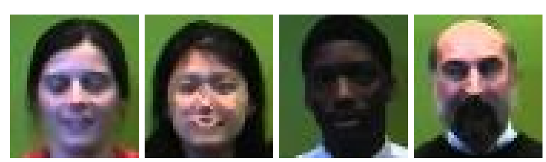

Fig. 12. Intentionally degraded images.

The subjective effect of retaining a various number of eigen-features from the color image can be evaluated in Fig. 13.

Fig. 13. (a) Original image. (b) Reconstructed image from 50 eigen-features/each (R, G, B).
(c) 100 features. (d) 500 features.

Table 1. Recognition score for the test lot of 1510 original color images

Number of features/color component		10	30	50	70	90	100	150	200	300	500	1000
RGB	Feature fusion	97.22	98.34	98.68	98.81	98.68	98.74	98.87	98.94	99.34	99.87	99.87
	Red	94.7	98.08	98.15	98.54	98.48	98.61	98.54	98.87	98.94	99.27	99.34
	Green	95.3	97.88	98.68	98.34	98.48	98.54	98.48	98.74	99.14	99.06	99.67
	Blue	94.1	97.75	98.15	98.21	98.01	97.88	98.01	98.21	98.34	98.74	98.74
	Decision fusion	95.23	98.08	98.54	98.68	98.48	98.48	98.48	98.81	98.87	99.4	99.47
(C_1,C_2)	Feature fusion	97.28	98.94	99.00	99.00	99.27	99.14	99.34	99.47	99.54	99.8	99.8
	C_1	95.1	98.21	98.61	98.68	98.74	98.81	98.81	99	99.4	99.4	99.4
	C_2	95.89	98.08	98.15	98.21	98.34	98.28	98.34	98.34	98.68	98.81	98.87

Table 2. Recognition score for the test lot of 1510 degraded color images

Number of features/color component		10	30	50	70	90	100	150	200	300	500	1000
Luminance		96.25	98.61	98.94	98.94	99	99	99	99.14	99.27	99.54	99.54
RGB	Feature fusion	97.4	98.48	99.00	99.00	98.94	98.94	99.14	99.47	99.54	99.87	99.87
	Red	95.36	98.61	98.87	98.81	98.87	98.94	98.94	99.07	99.27	99.6	99.54
	Green	95.7	98.34	99.47	99.07	99.07	99.14	99.47	99.54	99.87	99.87	99.87
	Blue	95.7	98.15	98.61	98.61	98.34	98.34	98.34	98.61	98.81	99.00	99.07
	Decision fusion	95.96	98.34	99.07	99.00	98.81	98.87	99.07	99.21	99.47	99.8	99.74
(C_1,C_2)	Feature fusion	97.75	99.21	99.21	99.34	99.21	99.47	99.47	99.67	99.8	99.8	99.8
	C_1	95.96	98.61	99.00	99.00	98.94	99.00	99.00	99.21	99.47	99.74	99.74
	C_2	96.29	98.21	98.48	98.48	98.61	98.61	98.68	98.68	98.87	99.07	99.21

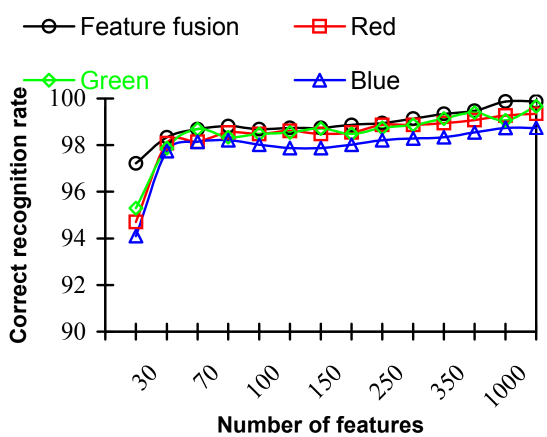

Fig. 14. Recognition score for the systems given in Figs. 8- 9.

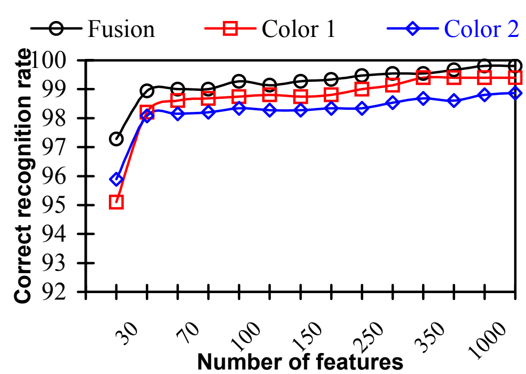

Fig. 15. Recognition score for the system given in Fig. 6.

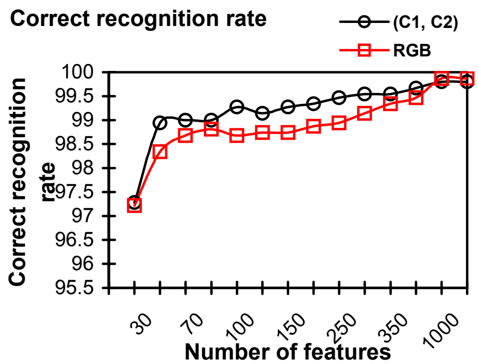

Fig. 16. Comparison of (R, G, B) and (C_1, C_2) best results.

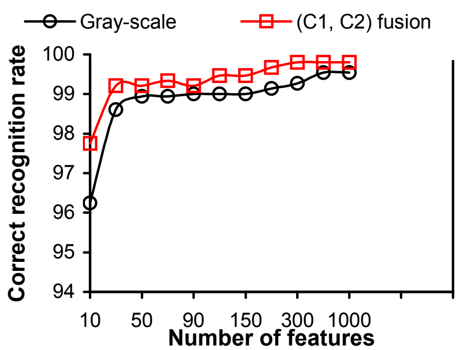

Fig. 17. Comparison of gray and 2D color image recognition performance for degraded images.

5 Concluding Remarks

1. We present a model of 2D color image representation for pattern recognition, using the KLT to project the 3D RGB space into an optimum color plane.
2. The mean square error of color dimensionality reduction (from 3 to 2) is about 3% only, for the considered applications.
3. Using the above 2D color optimized representation, instead of the 3D color space, one can significantly reduce the computational effort for color image processing, by preserving almost all information content.
4. The model has exciting applications for color face recognition and color image segmentation.
5. One proposes a color face recognition system in the 2D color space, using feature fusion and a multiple neural module classifier. We compare this model with two schemes, based on 3D color input vectors.
6. Best results of color face recognition correspond to the new model (feature fusion of the C_1 and C_2 color components and concurrent neural classifier, shown in Fig. 6). This variant is superior both to the feature fusion of R, G, B components and also to the decision fusion of the same color channels.
7. One can remark the role of *color* for face recognition in the case of degraded images (see comparison between gray-scale (luminance) images and (C_1,C_2) color component fusion in Table 2 and Fig. 17).
8. In the case of degraded images, by retaining only C_1 component, one obtains better results than using the luminance.
9. An application of color image segmentation in the 2D color space using neural pixel clustering (with a circular SOM) is also given.
10. The proposed 2D color conversion model may have wide applications in the areas of color-based pattern recognition.

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A Neuro-Fuzzy Approach to Classification of ECG Signals for Ischemic Heart Disease Diagnosis

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A Neuro-Fuzzy Approach to Classification of ECG Signals for Ischemic Heart Disease Diagnosis

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ABSTRACT

The paper focuses on the neuro-fuzzy classifier called ***Fuzzy-Gaussian Neural Network (FGNN)*** *to recognize the ECG signals for Ischemic Heart Disease (IHD) diagnosis. The proposed ECG processing cascade has two main stages: (a) Feature extraction from the QRST zone of ECG signals using either the Principal Component Analysis (PCA) or the Discrete Cosine Transform (DCT); (b) Pattern classification for IHD diagnosis using the FGNN . We have performed the software implementation and have experimented the proposed neuro-fuzzy model for IHD diagnosis. We have used an ECG database of 40 subjects , where 20 subjects are IHD patients and the other 20 are normal ones. The best performance has been of 100% IHD recognition score. The result is exciting as much as we have used only one lead (V5) of ECG records as input data, while the current diagnosis approaches require the set of 12 lead ECG signals!*

1 INTRODUCTION

The *Ischemic (Ischaemic) Heart Disease (IHD)*, otherwise known as Coronary Artery Disease, is a condition that affects the supply of the blood to the heart. IHD is the most common cause of death in several countries around the world. Recently, there are many approaches involving techniques for computer processing of 12 lead electrocardiograms (ECG), in order to diagnose a certain disease. A first group of methods to interpret the ECG significance uses a morphological analysis. For example, myocardial ischemia may produce a flat or inverted T wave, that is classical narrow and symmetrical. A second group of techniques for computer analysis of ECG uses statistical models. In [2], a statistical model and the corresponding experimental results are presented for the classification of ECG patterns to diagnose the Ischemic Heart Disease (IHD). Last years, a third category of methods corresponding to *neural models* becomes a powerful concurrent to statistical ones for ECG signal classification [5 - 7].

On the other side, the hybrid systems of *fuzzy logic* and *neural networks* [4] often referred as *fuzzy neural networks)* represent exciting models of *computational intelligence* with direct applications in pattern recognition, approximation, and control. We further perform the ECG signal classification for IHD diagnosis using the neuro-fuzzy classifier called **Fuzzy-Gaussian Neural Network (FGNN)**, that has been proposed in [1] by Neagoe and Iatan for face recognition. FGNN has been obtained as a *modified version* of the fuzzy neural network described by Chen and Teng in [3], as identifier in control systems; this network is transformed in [1] from an *identifier* into the *performing classifier* called *Fuzzy Gaussian Neural Network (FGNN).* We have applied this model here in an ECG recognition cascade for IHD diagnosis having the following processing stages: (a) feature extraction using either Principal Component Analysis (PCA) or Discrete Cosine Transform (DCT); (b) FGNN as a classifier. The results of computer simulation are given.

2 FUZZY GAUSSIAN NEURAL NETWORK (FGNN)

2.1 Architecture

The four-layer structure of the Fuzzy-Gaussian Neural Network (FGNN) described in [1] is shown in Fig. 1. It represents a modified version the fuzzy neural network presented in [3], by transforming the function of approximation into a function of *classification*. The change affects only the equations of the fourth layer, while the structure diagram is similar. Its construction is based on fuzzy rules of the form

$\Re_j$: If x_1 *is* $A_1{}^j$ *and* x_2 *is* $A_2{}^j$ ... *and* x_m *is* $A_m{}^j$, *then* y_1 *is* $\beta_1{}^j$, …, y_M *is* $\beta_M{}^j$,

where m is the dimension of the input vectors (number of retained features), and j is the rule index (j=1,…, K). The number of output neurons (of the fourth layer) corresponds to the number of classes and it is equal to M. The FGNN keeps the advantages of the original fuzzy net described by Chen and Teng [3] for identification in control systems: (a) its structure allows us to construct the fuzzy system rule by rule; (b) if the prior knowledge of an expert is available, then we can directly add some rule nodes and term nodes; (c) the number of rules do not increase exponentially with the number of inputs; (d) elimination of redundant nodes rule by rule.

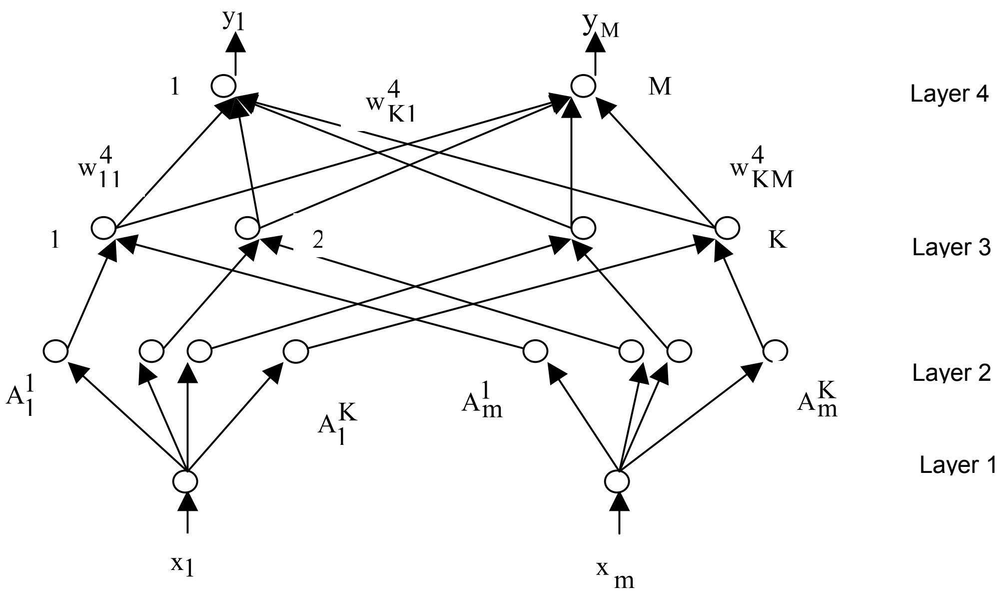

Figure 1. Structure of FGNN

Each neuron performs two actions using two different functions. The first is the aggregation function $g^k(\ )$, which computes the net input

Net input= $g^k\left(x^k; W^k\right)$,

where the superscript indicates the layer number (k=1, .., 4), x^k is the input vector and W^k is the weight vector. The second function is the nonlinear activation function $f^k(\ )$, which gives

Output= $O_i^k = f^k\left(g^k\right)$,

where O_i^k is the i-th output of the k-th layer.

2.2 Basic Equations

• Input level (level 1)

The neurons of the first level only transmit the information to the next level. The output

$Op_i^1 = x_{pi}^1$ (i=1, …, m)

is equal to the input, m is the number of neurons belonging to the firs level and p is the index of the input vector (p=1, …,K). The corresponding equations are $g_{pi}^1\left(x_{pi}^1\right) = x_{pi}^1$, (1)

$$O_{pi}^1 = f_i^1\left(g_{pi}^1\right) = g_{pi}^1\left(x_{pi}^1\right),\ i=1, .., m. \tag{2}$$

•Linguistic Term Layer (level 2)

Each neuron performs a **Gaussian** membership function

$$g_{pij}^2\left(x_{pi}^2; m_{ij}; \sigma_{ij}\right) = -\frac{\left(x_{pi}^2 - m_{ij}\right)^2}{\sigma^2_{ij}}, \tag{3}$$

$$O_{pij}^2 = f_{ij}^2\left(g_{pij}^2\right) = \exp\left(g_{pij}^2\right) = \exp\left[-\frac{\left(x_{pi}^2 - m_{ij}\right)^2}{\sigma^2_{ij}}\right] \tag{4}$$

where the corresponding weights to be refined m_{ij} and σ_{ij} denote the mean and variance with respect to A_i^j (i= 1, …, m, j=1, …, K). The number of neurons characterizing this level is m*K. Each input x_{pi}^2 is transformed by this layer into a *fuzzy membership degree*.

• Rule Layer (level 3)

This layer computes the antecedent matching by the product operation, according to the relations

$$g_{pj}^3\left(x_{pij}^3; W_{ij}^3\right) = \prod_{i=1}^{n} W_{ij}^3 * x_{pij}^3, \tag{5}$$

$$O_{pj}^3 = f_j^3\left(g_{pj}^3\right) = g_{pj}^3\left(x_{pij}^3; W_{ij}^3\right), \tag{6}$$

where W_{ij}^3 is the connection weight between the i-th node of the second level (i=1, …, m) and the j-th neuron of the third level (j=1, .., K). Assume $W_{ij}^3=1$, $(\forall)$ i=1, .., m, j=1, …, K.

•Output Level (level 4)

This level performs the defuzzification

$$g_{pj}^4\left(x_{pi}^4; W_{ij}^4\right) = \sum_{i=1}^{K} W_{ij}^4 * x_{pi}^4. \tag{7}$$

We introduce at this level a sigmoid activation function in order to apply the FGNN for classification

$$y_{pj}^4 = f_j^4\left(g_{pj}^4\right) = \frac{1}{1 + \exp\left(-\lambda * g_{pj}^4\left(x_{pi}^4; W_{ij}^4\right)\right)} \tag{8}$$

where W_{ij}^{4} is the connection between the neuron i (i=1, …, K) of the third level and the neuron j (j=1, … , M) of the fourth level.

The *FGNN supervised training algorithm* is of type "back-propagation".

3 EXPERIMENTAL RESULTS

3.1 ECG Database

For experimenting the proposed FGNN model, we have used an ECG database of 40 subjects : 20 patients of Ischemic Heart Disease (IHD) and other 20 normal subjects. The ECG database is divided into the training lot and the test lot, each with 20 subjects of both categories (10 normal and 10 with IHD). We have considered that the *significant information for IHD diagnosis is concentrated on the QRST zone of the lead V5 only.* For acquisition of ECG signals, a sampling frequency of 1000 Hz and a resolution of 11 bits/sample have been chosen. A sequence of heartbeats of 9.9 s of the lead V5 has been stored for each subject (9999 samples). First ECG processing step has consisted of extracting the useful information from a record, namely construction of a characteristic waveform called prototype [2], [8]. The *selected QRST* zone of the prototype has been normalized to n=128 samples (Figs. 2 and 5).

3.2 Feature Extraction

- **Feature extraction using PCA**

The *Principal Component Analysis (PCA)* stage is equivalent to the computation of the Karhunen-Loeve Transform [8]. We have computed the covariance matrix of the whole training set of 20 vectors $\mathbf{X} \in \boldsymbol{R}^{128}$, the *eigenvalues* and the *eigenvectors.* We have ordered the eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_{127} \geq \lambda_{128}$, and have computed the energy preservation factor E, by retaining only "m" eigenvalues. The variation of the factor E as a function of **m** is given in Table 1; for example, we can reduce the space dimension from 128 to 28, by preserving 100 % of the signal energy (Table 1). Examples of PCA (amplitude spectrum) are given in Figs. 3 and 6.

- **Feature extraction using DCT**

The *Discrete Cosine Transform (DCT)* applied for feature extraction has the advantage of reducing the computational effort (there are several algorithms available [9]), but it leads to a slightly less energy-preserving factor by comparison to PCA. The simulation results given in Table 1 show that one can reduce the space dimension from 128 to 28 using DCT, by preserving 98.42% of the signal energy. Examples of DCT (amplitude spectrum) are given in Figs. 4 and 7.

3.3 Classification with FGNN for IHD Diagnosis

The FGNN classifier is applied for IHD diagnosis in the m- dimensional space of the retained features. We have experimented the neuro-fuzzy classifier for the two variants of feature extraction (PCA and DCT) choosing the following numbers of retained features: m=10, 28, 40 and 50. The recognition performances are shown in Table 2 and Fig.8.

4 CONCLUDING REMARKS

1. The paper presents an ECG classification approach for IHD diagnosis using a neuro-fuzzy model called *Fuzzy-Gaussian Neural Network (FGNN).*
2. The ECG processing cascade has two main stages: (a) feature extraction using either PCA or DCT; (b) ECG pattern classification using FGNN.
3. The promising classification performance of FGNN may be explained by the fact that the classifier is a *hybrid system* of fuzzy logic and a powerful Gaussian network.
4. By choosing PCA as a feature selection technique, for the training lot of 20 ECG-QRST prototypes (10 normal subjects and 10 afflicted with IHD), one can reduce the space dimension from 128 to 28 by preserving 100% of the signal energy (Table 1). By considering that the initial 12 lead ECG record during 9.9 s is reduced to the QRST zone of one lead only (128 samples), the real compression is from 12 x 9 900=118 800 samples to 28 coefficients, implying a compression ratio of 4 242:1!
5. If one chooses the DCT for the same space dimensionality reduction, the energy preservation ratio decreases to 98.42% (Table 1).
6. In Table 2 and Fig. 8, one can evaluate *the very good recognition performance (100%*!) of the FGNN by choosing PCA as a feature extraction stage with m=50 features. *The result is exciting as much as we have used only one lead (V5) of ECG records as input data, while the current approaches use the computer processing of 12 lead ECG signals for diagnosis!*
7. For the same number of retained features "m", the DCT usually leads to a less recognition rate than PCA (for example, for m=50, one obtains a recognition score of 90% for DCT and 100% for PCA; for m=28, one obtains a recognition score of 90% for DCT and 95% for PCA).
8. Usually, by increasing the number of retained features "m", the recognition score increases (Table 2 and Fig. 8).

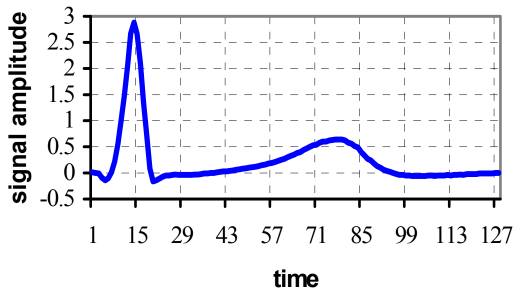

Fig. 2. ECG-QRST prototype corresponding to a normal subject

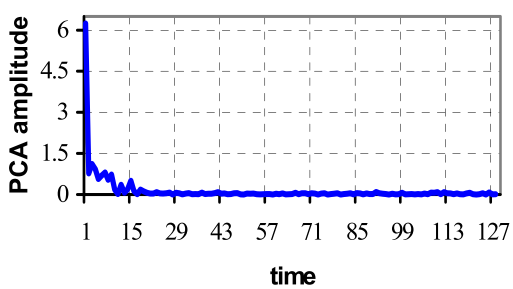

Fig. 3. PCA of the prototype given in Fig. 2.

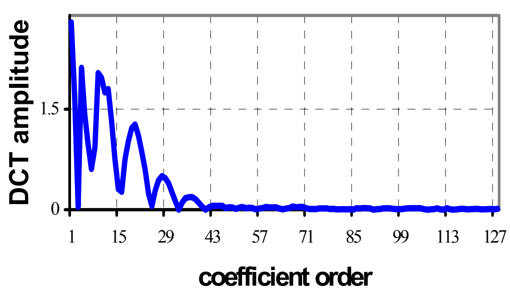

Fig. 4. DCT of the prototype given in Fig. 2.

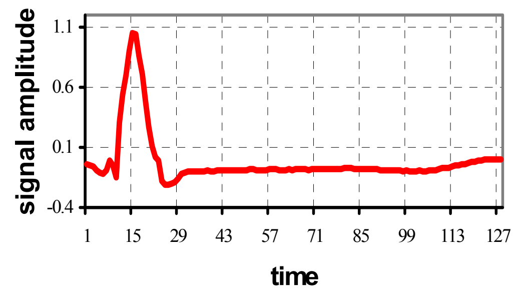

Fig. 5. ECG-QRST prototype corresponding to a patient afflicted with IHD (remark the flat T area)

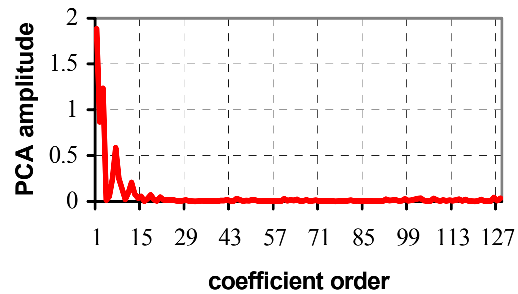

Fig. 6. PCA of the prototype given in Fig. 5

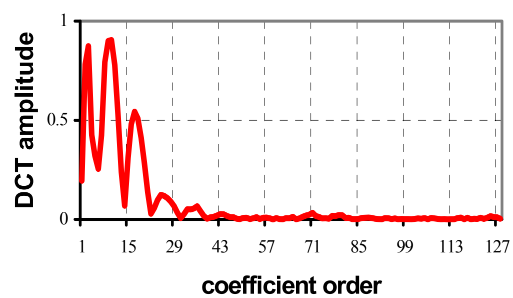

Fig. 7. DCT of the prototype given in Fig. 5

Table 1. Energy preservation factor of PCA versus DCT as a function of the number of features m .

Number of Features (m)		10	28	30	38	40	48	50	58	60	68
Energy preservation factor E(%)	PCA	99.64	100	100	100	100	100	100	100	100	100
	DCT	76.14	98.42	98.79	99.58	99.65	99.84	99.86	99.90	99.91	99.93

Table 2. Recognition score of the FGNN classifier as a function of the number of features m.

Number of retained principal components m	**Type of feature extraction**	**Recognition score for the training lot (%)**	**Recognition score for the test lot (%)**	**Number of training epochs**
10	PCA	95	85	402
10	DCT	95	85	346
28	PCA	95	95	1837
28	DCT	100	90	785
40	PCA	100	90	708
40	DCT	100	90	379
50	PCA	100	100	1041
50	DCT	100	90	183

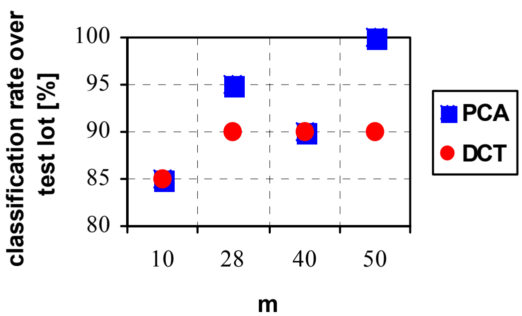

Fig. 8. Recognition score for IHD (%) over the test lot as a function of the number of features

9. The DCT requires a less computational complexity than PCA, since it has several fast algorithms available.

10. Moreover, the network training time decreases for DCT by comparison to PCA (Table 2). For example, choosing m=50 features, the number of necessary training epochs is 1041 for PCA, leading to a recognition rate of 100% and the number of epochs becomes 141 for DCT, leading to the recognition rate of 90%.

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Data Fusion and Neural Networks for Disaster Forecasting: Flood Prediction Case

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ABSTRACT

A model of Adaptive Data Fusion Reservoir Inflow Forecasting using Concurrent Neural Networks (ADAFIFCON) is presented. It uses a fusion of previous rainfall and reservoir inflow data. The system consists of three backpropagation neural networks. Each neural module is trained to estimate a specific class of data dynamics: low, medium and high gradients. The decision fusion module uses a concurrent strategy. The model is applied to forecast the reservoir inflow for St-Jean Lake, Quebec, Canada. The method may be applied for disaster prediction and management for NATO (Science for Peace) Projects.

1.0 INTRODUCTION

Multisensor data fusion is an emerging technology drawn from artificial intelligence, pattern recognition, statistical estimation, and other areas. Fusion multisensor data has significant advantages over simple source data, obtaining a more accurate estimate of a physical phenomenon. Data fusion provides new modelling opportunities in other areas of the physical and social sciences, which includes geographical and environmental research.

In hydrological research, a significant effort has been concentrated to river flow prediction task. Flash floods are dangerous phenomena, which have produced in the past important economic losses and in some cases, life losses. A flood warning systems is a technical way to reduce such risks. If the hydrological system includes a dam equipped with control gates, improved criteria for gates operation during the flood can be assessed. There have been many recent papers and contributions regarding the applications of backpropagation neural networks (BPNN) for river discharge (or reservoir inflow) forecasting.

We further present a model of **A**daptive **Da**ta **F**usion Reservoir **I**nflow **F**orecasting using **Co**ncurrent **N**eural **N**etworks (ADAFIFCON). It uses a fusion of rainfall and inflow data (previous samples of rainfall and reservoir inflow data). This multi-system consists of a set of three concurrent backpropagation neural networks, corresponding to the three classes of rainfall sample gradients: low, medium and high. The model is applied for the reservoir of St-Jean Lake, Quebec, Canada.

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2.0 ADAPTIVE DATA FUSION RESERVOIR INFLOW FORECASTING WITH CONCURRENT NEURAL NETWORKS (ADAFIFCON)

We propose the data fusion system for reservoir inflow forecasting (ADAFIFCON) shown in Figure 1. It consists of a set of three concurrent backpropagation neural networks. Each neural module is designed to estimate a specific class of data dynamics: low, medium and respectively high gradients.

The input data which are amalgamated by the data fusion system corresponds to:

- the previous samples of the reservoir inflow:

  y[n-1], y[n-2], y[n-3], … y[n-q]

- the previous rainfall samples:

  x [n-1], x [n-2], … x [n-p]

The training set (consisting of rainfall data and corresponding inflow data) is divided before training into three time domains : D_L, D_M and D_H, The classification of a given sample pair { x[n] , y[n] } is given by the following decision rule based on the gradient of the rainfall adjacent samples :

$$0 < | x[n] - x[n-1] | \leq \alpha \quad \Rightarrow \quad \{x[n], y[n]\} \in D_L$$

$$\alpha < | x[n] - x[n-1] | \leq \beta \quad \Rightarrow \quad \{x[n], y[n]\} \in D_M$$

$$\beta < | x[n] - x[n-1] | \quad \Rightarrow \quad \{x[n], y[n]\} \in D_H \qquad (\text{with } 0< \alpha <\beta),$$

where D_L, D_M and D_H are the time domains corresponding to the labels ***low***, ***medium*** and ***high***. Each neural network (L, M, or H) is trained using the samples of the corresponding domain (subset), characterized by its rainfall dynamics (D_L, D_M or D_H).

After training, the three neural modules (Figure 1) estimate in parallel the output task (reservoir inflow). The decision fusion module uses a concurrent strategy by choosing at each step the best fitting neural module. Namely, at each forecasting step one chooses the neural network which obtained the best estimation accuracy at the previous step.

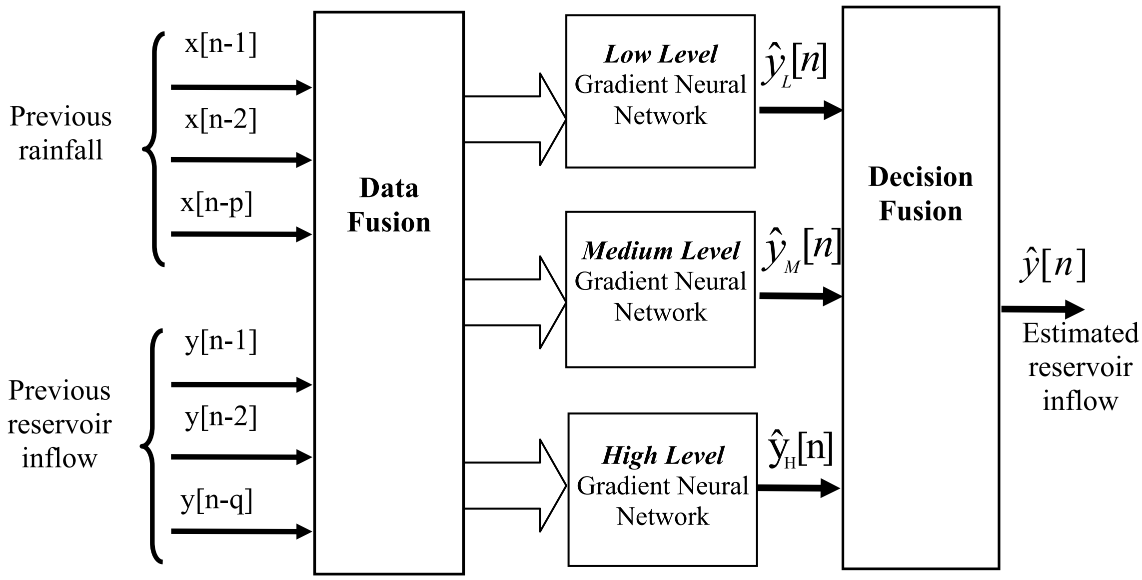

Figure 1: Adaptive data fusion reservoir inflow forecasting with concurrent neural networks (ADAFIFCON)

3.0 EXPERIMENTAL RESULTS

3.1 Hydrological and meteorological datasets

We considered the quarter monthly inflows data as well as corresponding rainfall data for the St-Jean Lake reservoir, Quebec, Canada. The data covered the period of the years 1953-1982.

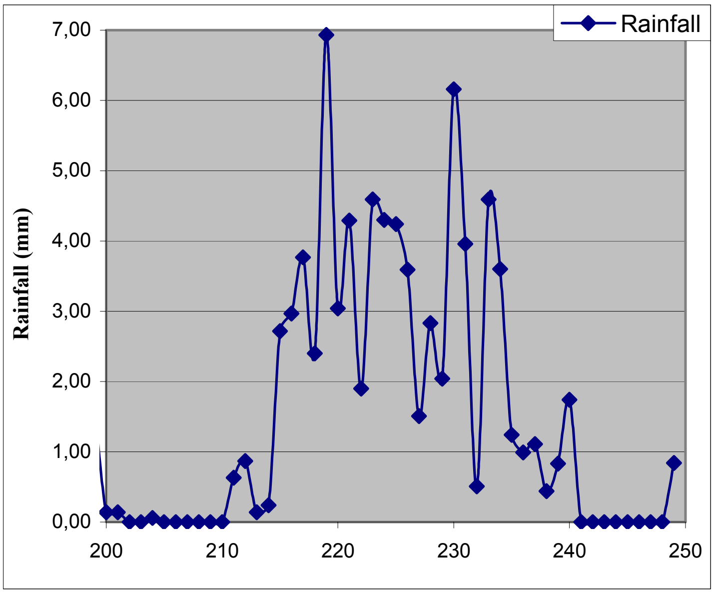

Figure 2: Observed rainfall

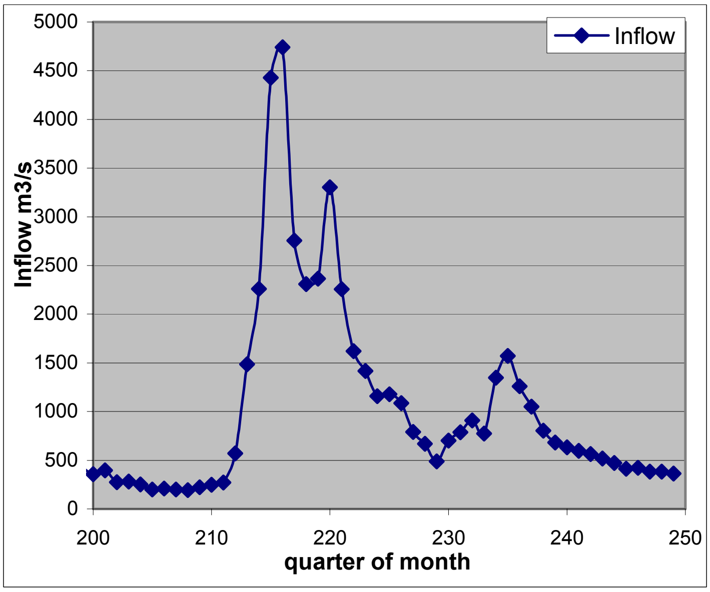

Figure 3: Observed reservoir inflow

In Figures 2 and 3 one can see an example of the observed rain-fall and the corresponding St-Jean Lake reservoir inflow. The sampling period is equal to a quarter of month.

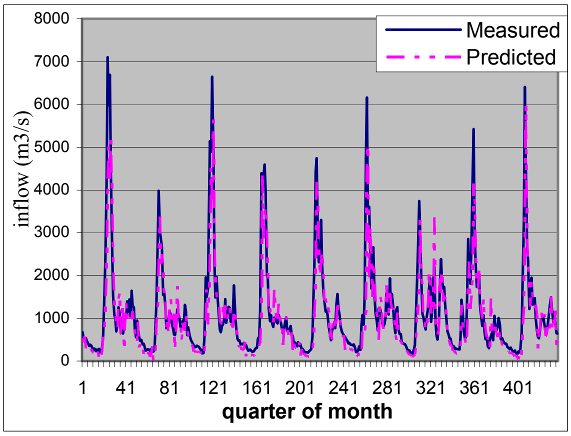

Figure 4: Measured vs. Predicted Inflows (m^3/s)

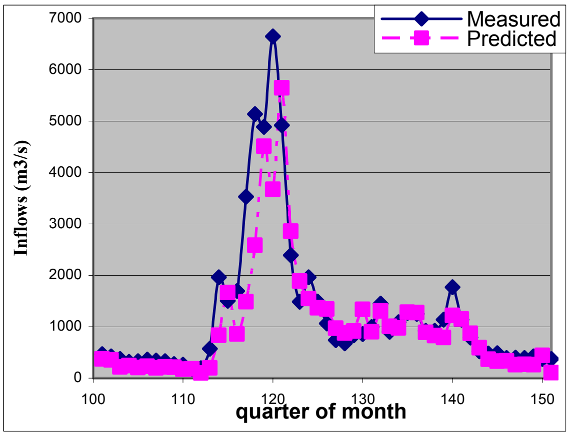

Figure 5: Measured vs. Predicted Inflows (m^3/s)

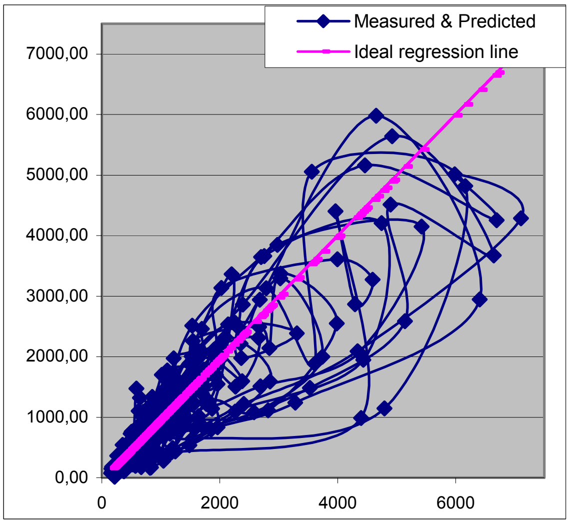

Figure 6: Measured and Predicted Inflows (in m^3/s)

3.2 Model evaluation

Each backpropagation neural module has a feedforward architecture with the following dimensions :

- number of input neurons equals the number of input data
- number of hidden neurons = 4
- one output neuron

We used a number of 100 training epochs. For performance evaluation, we consider the following measures:

- the root mean square error (Rmse) between the ideal and the forecasted reservoir inflow data
- the correlation coefficients of the ideal inflow sequence and the estimated one.

The experimental results are given in Table 1 and Figures 4-6.

Table 1: Performance evaluation of the ADAFIFCON model

	Inputs		Rmse (m^3/s)	Correlation
	Reservoir Inflow	Rainfall	Test.	Test.
ADAFIFCON (Multi-system) (3-nets)	y[n-1], y[n-2], y[n-3]	x[n], x[n-1], x[n-2]	0.596	0.8552
	y[n-1], y[n-2], y[n-3]	none	0.627	0.8532
	y[n-1], y[n-2], y[n-3]	x[n-1], x[n-2]	0.588	0.8585
	y[n-1], y[n-2]	x[n], x[n-1]	0.591	0.8558
	y[n-1], y[n-2]	x[n-1], x[n-2]	0.580	0.8629
	y[n-1], y[n-2]	none	0.616	0.8536
	y[n-1], y[n-2]	x[n-1]	0.592	0.8479
Mono-system (single net)	y[n-1], y[n-2], y[n-3]	x[n], x[n-1], x[n-2]	0.669	0.8506
	y[n-1], y[n-2], y[n-3]	none	0.626	0.8539
	y[n-1], y[n-2], y[n-3]	x[n-1], x[n-2]	0.661	0.8560
	y[n-1], y[n-2]	x[n], x[n-1]	0.679	0.8556
	y[n-1], y[n-2]	x[n-1], x[n-2]	0.648	0.8576
	y[n-1], y[n-2]	x[n-1]	0.653	0.8581
	y[n-1], y[n-2]	none	0.627	0.8560
Naive	y[n-1]	none	0.628	0.8570

The best result corresponds to the case of using 4 inputs: 2 previous rainfall samples {x[n-1], x [n-2]} and 2 previous inflow samples {y [n-1], y [n-2]}. The advantage of using the proposed multiple network system over a single network system is obvious. The case of naïve prediction is also considered for comparison.

The method may be applied for disaster prediction and management in NATO Science for Peace Projects.

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Real Time Face Recognition Using Decision Fusion of Neural Classifiers in the Visible and Thermal Infrared Spectrum

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Abstract

This paper is dedicated to multispectral facial image recognition, using decision fusion of neural classifiers. The novelty of this paper is that any classifier is based on the model of Concurrent Self-Organizing Maps (CSOM), previously proposed by first author of this paper. Our main achievement is the implementation of a real time CSOM face recognition system using the decision fusion that combines the recognition scores generated from visual channels {(R, G, and B) or Y} with a thermal infrared classifier. As a source of color and infrared images, we used our VICFACE database of 38 subjects. Any picture has 160 x 120 pixels; for each subject there are pictures corresponding to various face expressions and illuminations, in the visual and infrared spectrum. The spectral sensitivity of infrared images corresponds to the long wave range of 7.5 – 13 μm. The very good experimental results are given regarding recognition score.

1. Introduction

The Self-Organizing Map (SOM) (also called Kohonen network) [1] is an artificial unsupervised neural network characterized by the fact that its neurons become specifically tuned to various classes of patterns through a competitive, unsupervised or self-organizing learning. The spatial location of a neuron in the network (given by its co-ordinates) corresponds to a particular input vector pattern. Similar input vectors correspond to the same neuron or to neighbor neurons. One important characteristics of SOM is that it can simultaneously perform the feature extraction and it performs the classification as well.

Starting from the idea to consider the SOM as a cell characterizing a specific class only, Neagoe proposed and evaluated in [2], [3], [4] a new neural recognition model called Concurrent Self-Organizing Maps (CSOM), representing a collection of small SOM units, which use a global winner-takes-all strategy. Each SOM is trained to correctly classify the patterns of one class only and the number of networks equals the number of classes. The CSOM model proved to have better performances than SOM, both for the recognition rate and also for reduction of the training time.

All over the world, governments and private companies are putting biometric technology at the heart of ambitious projects, ranging from access control and company security to high-tech passports, ID cards, driving licenses, and company security. One of most important areas of biometric technology is face recognition; this is still a highly challenging task in pattern recognition and computer vision [5], [6]. Face recognition based only on the visual spectrum has shown difficulties in performing consistently under uncontrolled operating conditions. Face recognition accuracy degrades quickly when the lighting is dim or when it does not uniformly illuminate the face [7], [8]. Light reflected from human faces also varies depending on the skin color of people from different ethnic groups. The use of thermal infrared (IR) images can improve the performance of face recognition under uncontrolled illumination conditions [9], [10], [11]. Thermal IR spectrum comprising mid-wave IR (3-5μm) and long-wave IR (8-12μm) bands has been suggested as an alternative source of information for detection and recognition of faces. Thermal IR sensors measure heat energy emitted, not reflected, from the objects. Hence thermal imaging has great advantages in face recognition in low illumination conditions or even in total darkness, where visual face recognition techniques fail.

Recently, it has been observed that classifiers of different types complement one another in classification performance [12], [13], [14]. This has led to a belief that by using classifiers of different types simultaneously, classification accuracy could be improved. The corresponding special technique of pattern recognition is **decision fusion**, by combining the classification powers of several classifiers. Ideally, the combination function should take advantage of the strengths of the individual classifiers, avoid their weaknesses, and improve classification accuracy. Classical methods for classifier combination [13] include intersection of decision regions, voting methods, prediction by top choice combinations, and use of Dempster-Shafer theory. In this paper, we apply Dempster-Shafer theory of evidence presented in [12], [15], for decision fusion face recognition.

Particularly, the problem becomes that of combining CSOM classifiers receiving visible spectrum information (color components or luminance) with a CSOM classifier using thermal infrared spectrum. One variant of decision fusion investigated here is to combine between the R, G, B channel data of color imagery and infrared (IR) channel; a second decision variant is the combination between the luminance channel Y and IR channel. In a previous paper [16], one uses two optimized color components for pattern recognition instead of the R, G, and B ones. Other approach uses a neural technique for feature extraction from (R, G, B) images [17]. Regarding IR channel, we focused our attention on long wave infrared (LWIR) imagery, in the spectral range of 7.5-13 µm. Thermal infrared imagery of faces is nearly invariant to changes in ambient illumination.

The paper is structured as follows.

Second section shows the essentials of Concurrent Self-Organizing Maps (CSOM) model.

Third section presents an algorithm of decision fusion of N CSOM classifiers using the application of Dempster-Shafer theory of evidence.

In the fourth section one proposes and evaluates a real time face recognition system, using the decision fusion based on Dempster-Shafer theory. This system combines the recognition scores generated from visual classifiers {(R, G, B) or Y} and long wave infrared (IR) CSOM classifier. The experimental results are given.

2. A Neural Pattern Classifier Composed by Concurrent Self-Organizing Maps (CSOM)

Concurrent Self-Organizing Maps (CSOM) [2], [3], [4] is a collection of small SOM modules, which use a global winner-takes-all strategy. Each module is trained to correctly classify the patterns of one class only and the number of networks equals the number of classes. The CSOM training technique is a supervised one, but for any individual net the SOM specific training algorithm is used. We built "K" training patterns sets and we used the SOM training algorithm independently for each of the "K" neural units. Namely, each SOM module is trained with the patterns characterized by the corresponding class label. The CSOM models for training and classification are shown in
Figure 1.

For the recognition, the test pattern has been applied in parallel to every previously trained SOM. The neural module providing the minimum distance neuron is decided to be the winner and its index becomes the class index that the pattern belongs to.

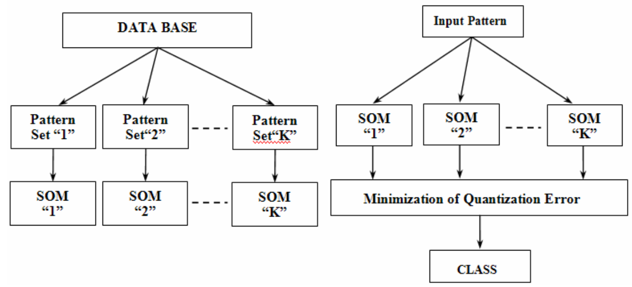

Figure 1: *The CSOM model.*
(a) Training phase. (b) Classification phase.

In fact, CSOM is a **system of systems** having improved performances over a single big SOM with the same number of neurons, both from the point of view of recognition accuracy and for reducing the training time as well [10], [11].

3. Decision Fusion of Neural Classifiers Using Dempster-Shafer Theory

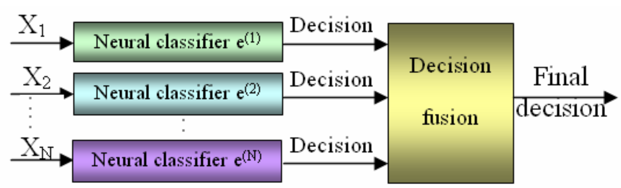

Figure 2: *Decision fusion of multiple concurrent neural modules.*

We further present an algorithm for decision fusion of multiple CSOM classifiers based on *Dempster-Shafer theory of evidence* presented in [12] and [15]. The novelty consists of adapting the theory for the case of CSOM classifiers. Consider the case of N concurrent modular neural classifiers (CSOM) denoted by $e^{(n)}$, where $n = 1, 2, \ldots, N$. Let $\boldsymbol{X}_k$ be the training data matrix for each class (neural module), $k = 1, 2, \ldots, K$, where K is the total number of classes. We will assume here equal amount of training for each of the classes. Also let θ_k be the label for each class k. Now, the feature extraction module of each classifier extracts a feature matrix $\mathbf{X}_k^{(n)}$. We define a modelling function *Ω(.)* which models each class so that

$$\Omega\left(\mathbf{X}_k^{(n)}\right) = U_k^{(n)};\ U_k^{(n)} = \left\{W_{k,i}^{(n)}\right\}$$

$k = 1, 2, \ldots, K$

$n = 1, 2, \ldots, N$

$i = 1, 2, \ldots, m$

Denote by $\left\{W_{k,i}^{(n)}\right\}$ the set of weight vectors corresponding to the neural module labeled with class "k" (for the classifier of index "n"). We denote by "m" the number of neurons of each module. Let **z** be an input test pattern which is modeled in a similar way

$\Omega(\mathbf{z}) = \mathbf{Z}$

For the case of a single classifier, the classification task is to assign class i to pattern **z** if

$D(\mathbf{U}_i, \mathbf{Z}) < D(\mathbf{U}_k, \mathbf{Z}) \ \forall k = 1, 2, \ldots, K \ (k \neq i)$,

where $\mathbf{U}_k$ is the model for each class k, and $\mathbf{U}_i$ being the nearest neighbor to **Z**. $D(.)$ is a distance measure between the test pattern model (**Z**) and the training pattern models for each class ($\mathbf{U}_k$, $k = 1, 2, \ldots, K$).

Assume now that we have N classifiers, so that each classifier operates on the test model independently to reach an independent decision.

Since for each classifier, the function $\Omega(.)$ models the patterns in the same manner, we propose the nearest neighbor distance $\overset{(n)}{\min_k}\left\{D\left(\mathbf{U}_k^{(n)}, \mathbf{Z}\right)\right\}$ as the evidence of our belief in the decision made by classifier n. Thus, the belief becomes a decreasing function (say $\psi(.)$) of this distance

$$m^{(n)}(i) = \Psi\left(-\left(\overset{(n)}{\min_k}\{D(\mathbf{U}_k, \mathbf{Z})\}\right)\right)$$

where $m^{(n)}(i)$ is our belief in classifier n for classifying test pattern **z** as class i.

One candidate for the function $\psi(.)$ could be the exponential function:

$$m^{(n)}(i) = \exp\left(-\lambda\left(\overset{(n)}{\min_k}\{D(\mathbf{U}_k, \mathbf{Z})\}\right)\right)$$

Hence the smaller the nearest neighbor distance measure, the greater is our belief in the decision of the classifier. In summary our algorithm works as follows:

1. Each class is modelled using the training data matrix $\mathbf{X}_k$, $k = 1, 2, \ldots, K$ and the function $\Omega\left(\mathbf{X}_k^{(n)}\right) = \mathbf{U}_k^{(n)}$.
2. Input test pattern **z** is also modelled using the same modelling function $\Omega(.)$, i.e. $\Omega(\mathbf{z}) = \mathbf{Z}$.
3. A distance measure, $D(.)$ is then used to evaluate the distance between **Z** and each of the models $\mathbf{U}_k^{(n)}$, $k = 1, 2, \ldots, K$.
4. For each classifier, a label is given to the test pattern **z** which corresponds to minimum distance measure
   $d_k^{(n)} = D\left(\mathbf{U}_k^{(n)}, \mathbf{Z}^{(n)}\right)$
   $n = 1, 2, \ldots, N$
   $k = 1, 2, \ldots, K$
5. We estimate our confidence in each classifier's decision as:
   $m_k^{(n)}(\mathbf{z}) = \exp(-\lambda d_k^{(n)})$

We then combine all evidences $m_k^{(n)}$ $n = 1, 2, \ldots, N$, $k = 1, 2, \ldots, N$ using Dempster-Shafer theory of evidence as follows

$$m(k) = \frac{\prod_{n=1}^{N} m_k^{(n)}(\mathbf{z})}{\sum_{k=1}^{K}\left(\prod_{n=1}^{N} m_k^{(n)}(\mathbf{z})\right)}$$

$k = 1, 2, \ldots, K$

6. Class label j is assigned to test pattern if
   $j = \max_{k=1}^{K}\{m(k)\}$; $k = 1, 2, \ldots K$.

Some special cases to be considered are:

a) if all classifiers reject a pattern, the consensus decision will then be rejection and thus our belief will be given to the frame of discernment $m(\Theta) = 1$.
b) if a subset of classifiers says M rejects a test pattern, then these classifiers will be excluded and the decision will be made on basis of remaining $(N - M)$ classifiers.

4. Real Time Face Recognition using Decision Fusion of CSOM Classifiers for Visible and Infrared Thermal Imagery

We further investigate *decision fusion* by combining matching scores generated by the visible and thermal infrared channels for face recognition. In Figure 3, the architecture of our implemented real-time multiple CSOM face recognition system is shown. The system uses a decision fusion based on Dempster-Shafer theory of evidence presented in section 3. The input information is provided by the visible and infrared channel classifiers. The two considered recognition system variants with decision fusion have either four or two input channels: (1) the color components (R, G, B) and the infrared channel (IR); (2) the luminance (Y) extracted from the input RGB color picture as well as the infrared channel (IR). Consequently, we have five CSOM classifiers.

Each CSOM contains a number of SOM modules equal to the number "K" of classes; each module has a circular architecture with "m" neurons.

For each of the considered decision fusion systems {(R, G, B, IR) and (Y, IR)}, we used two variants ("a" and "b") for choosing the rejection threshold.

For experimental evaluation, we have used the face database called VICFACE made by the team led by Prof. Victor Neagoe, Dept. of Electronics, Telecomm. and Information Technology, Polytechnic University of Bucharest, Romania. The face database has 228 images taken under frontal uniform illumination, and other 228 pictures taken using a nonuniform (top and lateral) illumination; the pictures correspond to 38 subjects. The color pictures are represented in RGB format (24 bits/pixel) and have a spatial resolution of 160x120 pixels. Most of the subjects are students of 23-25 year old (Figure 4). For frontal illumination, each subject is represented by 6 pictures, two for each of the three expressions: normal, happiness and sadness (Figure 5).

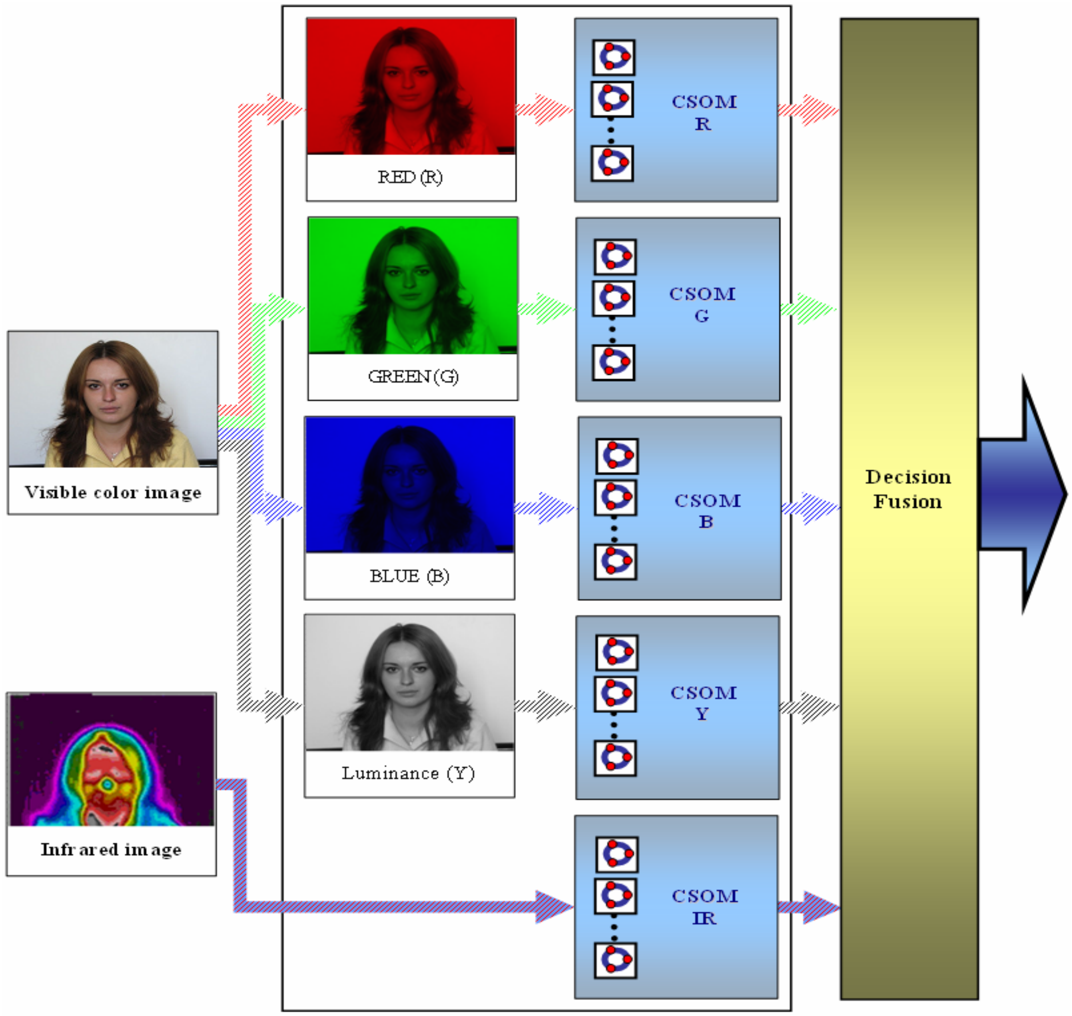

Figure 3: *Architecture of real time multiple CSOM face recognition system using visible and thermal infrared imagery.*

The infrared section of VICFACE database is composed by 456 thermal infrared images of 160 x 120 pixels; they are obtained using the FLIR ThermaCAM B2.

The spectral sensitivity of infrared images is in the long wave range of 7.5 – 13 µm. In Figure 4 there are given a few examples of color and infrared images for five subjects.

Figure 4: *Visual and infrared images corresponding to five subjects of VICFACE database.*

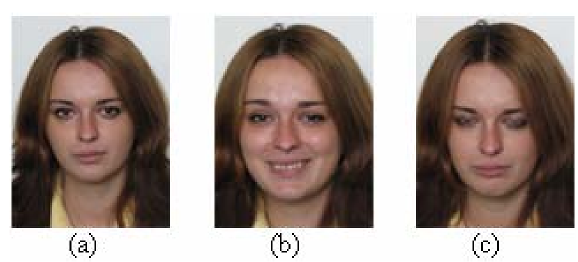

Figure 5: *Facial expressions of the same subject: (a) normal, (b) happiness, (c) sadness.*

The experimental results given in Tables 1 and 2, as well as in Figs. 6 and 7are self-explanatory; we compare CSOM, SOM and NP (Nearest Prototype) classifiers for IR facial image recognition.

Table 1: *Recognition score of CSOM versus SOM for thermal facial image recognition (without feature extraction).*

	1x38	2x38	3x38	4x38	5x38
CSOM	99.12	99.12	100	100	100
SOM	62.28	90.35	93.86	97.37	98.25
Nearest Prototype	98.25	98.25	98.25	98.25	98.25

Table 2: *Recognition score of CSOM versus SOM for thermal facial image recognition (PCA with p=100 retained features/picture).*

	1x38	2x38	3x38	4x38	5x38
CSOM	99.12	99.12	99.12	100	100
SOM	60.52	86.84	91.22	94.73	94.73
Nearest Prototype	97.37	97.37	97.37	97.37	97.37

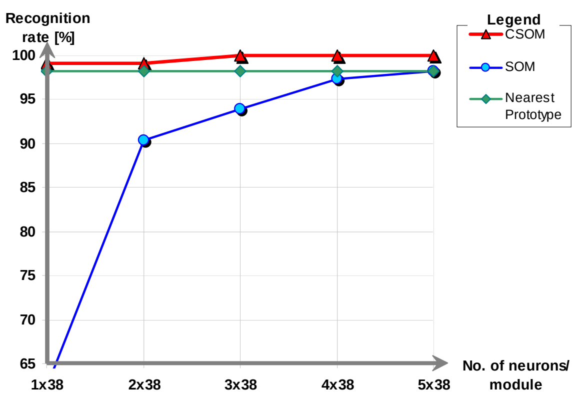

Figure 6 : *Recognition score of CSOM/SOM for thermal facial image recognition (without feature extraction).*

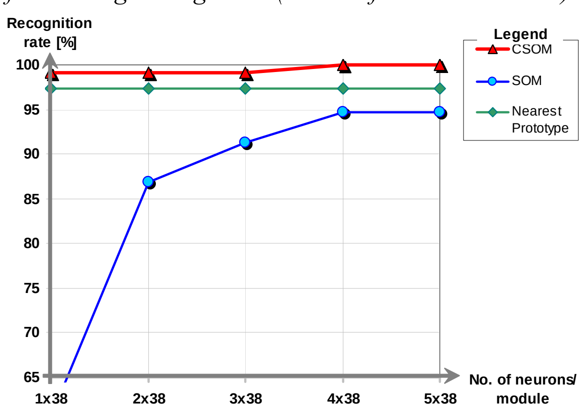

Figure 7: *Recognition score of CSOM/SOM for thermal facial image recognition (PCA with p=100 retained features/picture).*

The face recognition scores using fusion of multispectral CSOM classifiers are given in Table 3.

Table 3: *Recognition score for decision fusion of visual and infrared thermal CSOM classifiers (K=38 modules; m=7 neurons/module; PCA with p=100 features/picture).*

Lighting	R	G	B	Y	IR	Fusion (R,G,B,IR)	Fusion (Y,IR)
Linear decreasing from frontal centre	99.12	99.12	99.12	98.25	97.37	100	100
Linear decreasing from right centre	98.25	98.25	99.12	98.25	97.37	100	100
Low level uniform frontal	99.12	99.12	99.12	99.12	99.12	100	100

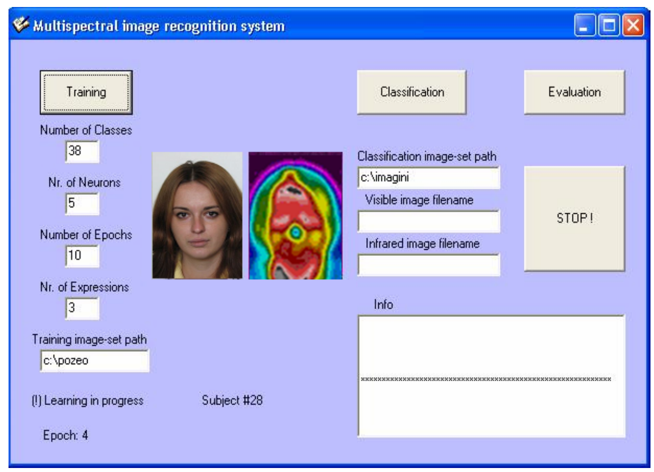

Figure 8: *Display of the experimental software recognition system.*

5. Concluding Remarks

1) This paper presents an approach to facial image recognition, using Dempster-Shafer theory for decision fusion of a special type of neural classifiers. Such a classifier is a set of neural modules based on the model of *Concurrent Self-Organizing Maps (CSOM)*, previously proposed by first author of this paper. Each neural classifier corresponds to a visual or thermal infrared channel. *CSOM* is a collection of small SOM modules ; it uses a global winner-takes-all strategy. Each neural unit is trained to correctly classify the patterns of one class only.
2) We evaluate the performances of CSOM versus SOM and NP (Nearest Prototype), for face recognition in the IR thermal spectrum. For the same number of neurons, CSOM has better *recognition performances* than SOM and NP.

3) From the point of view of *training time*, the advantage of CSOM over SOM is obvious. For "K" classes, the training time of CSOM is "K**"** times less than that of the corresponding SOM with the same number of neurons.
4) We performed an implementation of a real time CSOM face recognition system using the decision fusion. The novelty consists of adapting the Dempster-Shafer theory for the case of CSOM classifiers. The system combines the recognition scores generated from visual channels {(R, G, B) or Y classifiers} with the thermal infrared (IR) classifier. Inclusion of the long wave infrared imagery in the decision fusion implies the nearly invariance of recognition performances of the system to changes in ambient illumination.
5) One obtains that, for many experimental cases, the recognition score for decision fusion is higher than the best score of the combination classifiers (Table 3).
6) Even the only fusion between luminance (Y) and infrared (IR) information is already very good; since then, the contribution of color seems to be small.
7) The decision fusion performance gains seem rather small since the IR performance is already very good, especially for a small number of neurons; someone can ask if the added complexity is worthwhile for a small addition of performance. However, we consider that the results promise to open an interesting window for applying our neural CSOM model in decision fusion for multispectral facial image recognition.
8) By increasing the number of subjects belonging to the facial image database, as well as by considering images taken from the outdoor environment, one expects to obtain a better evaluation of the proposed fusion model performances for face recognition.

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Concurrent Self-Organizing Maps for Supervised/Unsupervised Change Detection in Remote Sensing Images

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***Abstract*—This paper proposes two approaches to change detection in bitemporal remote sensing images based on concurrent self-organizing maps (CSOM) neural classifier. The first one performs change detection in a supervised way, whereas the second performs change detection in an unsupervised way. The supervised approach is based on two steps: 1) concatenation (CON); and 2) CSOM classification. CSOM classifier uses two SOM modules: 1) one associated to the class of change; and 2) the other to the class of no-change for the generation of the training set. The unsupervised change detection approach is based on four steps: 1) image comparison (IC), consisting of either computation of difference image (DI) for passive sensors or computation of log-ratio image (LRI) for active sensors; 2) unsupervised selection of the pseudotraining sample set (USPS); 3) concatenation (CON); and 4) CSOM classification. The proposed approaches are evaluated using two datasets. First dataset is a LANDSAT-5 TM bitemporal image over Mexico area taken before and after two wildfires, and the second one is a TerraSAR-X image acquired in the Fukushima region, Japan, before and after tsunami. Experimental results confirm the effectiveness of the proposed approaches.**

***Index Terms*—Concurrent self-organizing maps (CSOM), multitemporal images, remote sensing images, supervised/unsupervised change detection.**

I. Introduction

CHANGE detection aims to identify land-cover changes between two coregistered remote sensing images acquired over the same geographical area at two different time instants [1]. In the literature, automatic change detection in digital images has become an increasingly important topic in the field of satellite image processing. Its applications play a relevant role in environmental studies, which requires knowledge about the evolution of slow phenomena and/or rapid abrupt changes. Examples of such phenomena are crop monitoring, land-cover shift analysis, deforestation monitoring, urban growth, and flood and fire control [2]–[6]. The relevance of such kind of analysis is confirmed by some activities carried out at European level such as the database of land changes between 2000 and 2006, based on standard CORINE land cover categories [7], [8] compiled by the European Environmental Agency (EEA).

In this paper, the focus is on damage assessment related to natural disasters application, such as changes caused by earthquakes [9], tsunamis [10], fires [11], etc. In the last decades, the frequency of such events has increased dramatically [12]; therefore, there is a rising interest in the scientific community for defining methods that can help in mitigating their effects and performing an automatic and fast assessment of the extension of the damages.

Numerous algorithms have been proposed for the automatic detection of changes [3], [10], [13]–[17]. These algorithms can be grouped into two large classes: *supervised* and *unsupervised* techniques. The supervised methods require a multitemporal ground truth information, but usually achieve higher performance. However the ground truth information collection requires a significant effort from the economical and practical view point [18]. The unsupervised approaches perform a direct comparison of the two multitemporal images and do not require any prior information about land-cover classes. Some examples of unsupervised methods can be found in [1], [16], and [18]. The most common approach to unsupervised change detection is based on thresholding of the image obtained after comparison. However, more unsupervised complex approaches exist. As an example in [13], an unsupervised approach is proposed which is based on support vector machine (SVM). Here, a pseudotraining set for SVM learning phase is generated in an unsupervised way by taking advantage of the a priori knowledge on the behavior of change and no-change class in the difference image.

Among the change detection approaches, in the last years, there have been proposed several techniques based on artificial neural networks (ANN) [15], [19], [20], which have been previously successfully applied for image analysis and segmentation tasks. ANN presents several advantages over other classification methods [6], such as: 1) automatic adjustment to the classified data, without requiring any a priori models; 2) they can be used as universal function approximators; and 3) they can be applied to nonlinear and discontinuous data. Among neural networks we recall here the interesting example of self-organizing map (SOM) (also called Kohonen network) as they have the peculiarity of

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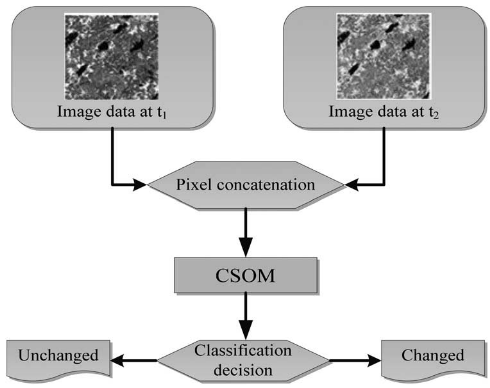


Fig. 1. Block scheme of the proposed supervised change detection approach.

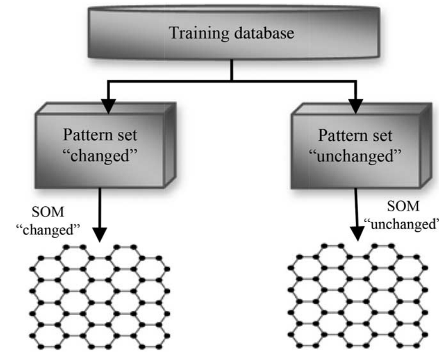


Fig. 2. CSOM training model.

being unsupervised. Neurons in them become specifically tuned to classes of patterns through a competitive, unsupervised or self-organizing learning [21].

Starting from the idea to consider the SOM as a cell characterizing a specific class, Neagoe and Ropot [22] proposed a new neural supervised classification model called concurrent SOM (CSOM). CSOM represents a collection of small SOM modules, which use a global winner-takes-all strategy. The mechanism is equivalent to generate by neural means an improved training set and to use this virtual training set as reference for a nearest neighbor (NN) classifier. In [23], CSOM model has been applied for static multispectral image classification. Here, we expand the use of to the detection of land-cover changes in time-series of remote sensing images in the context of both a supervised and an unsupervised change detection. The supervised approach consists of two steps: 1) concatenation of multitemporal image features; and 2) classification by CSOM. The unsupervised approach is based on four steps: 1) image comparison; 2) unsupervised generation of the pseudotraining set; 3) concatenation of multitemporal image features; and 4) classification by CSOM.

II. Proposed Supervised Change Detection Approach Based on CSOM

The proposed supervised change detection approach is based on: 1) concatenation of multitemporal image features (CON); and 2) CSOM classification (Fig. 1). We will refer to it as concatenation-based CSOM ($\mathrm{C^2SOM}$).

A. Concatenation

Feature concatenation is used to build the feature vector to be given as input to the CSOM classifier [20]. Let $A^T = [a_1 \ldots a_n]^T$ and $B^T = [b_1 \ldots b_n]^T$ be the n-dimensional feature vectors characterizing each spatial position in the images acquired at time t_1 and t_2, respectively. After concatenation, each spatial position will be modeled by a $2n$-dimensional feature vector V^T defined as

$$V^T = \left[A^T B^T\right] = [a_1 \ldots a_n \; b_1 \ldots b_n]^T. \tag{1}$$

B. CSOM Classification

The classification step is performed by the CSOM neural classifier [22], [23] extended to the use in the multitemporal domain. To this end, CSOMs combines SOM modules in a new complex network, which uses a winner-takes-all strategy for assigning the output class [22]. The number of SOM modules equals the number of classes (for change detection, one has two classes). Each SOM is trained in an unsupervised manner to correctly classify the patterns of one class only (i.e., change or no-change). Thus each SOM is trained with the subset of samples having the same class label as SOM label (Fig. 2). The global training algorithm is supervised, but each SOM uses an unsupervised training technique.

The CSOM technique is equivalent to substitute the real training samples by SOM generated virtual samples and then to apply the NN classifier using as reference all the pseudotraining samples. After CSOM training, each $2n$-dimensional input vector is assigned to the change or no-change class according to the label of the nearest CSOM neuron by minimizing the Euclidean distance.

III. Proposed Unsupervised Change Detection Approach Based on CSOM

The proposed unsupervised change detection approach is based on four steps: 1) image comparison (IC); 2) unsupervised generation of the pseudotraining set (USPS); 3) concatenation of multitemporal image features (CON); and 4) classification by CSOM (Fig. 3).

A. Multitemporal IC

Let us consider a generic pixel of the two considered n-dimensional images. Comparison is performed in different ways according to whether the multitemporal images are acquired by active or passive sensors.

In the case of multispectral images acquired by passive sensors comparison can be performed by computing the magnitude of the spectral change vectors (SCV) obtained by standard change vector analysis (CVA) approach as [18]

$$d = \sqrt{\sum_{i=1}^{n} (b_i - a_i)^2} \tag{2}$$

where d is the SCV magnitude image. In such image, changed samples assume large values, whereas unchanged samples assume small values.

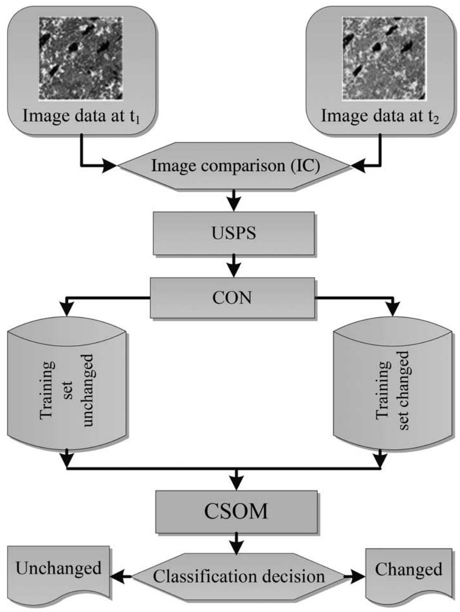


Fig. 3. Block scheme of the proposed unsupervised change detection approach.

In the case of images acquired by active sensors like synthetic aperture radar (SAR) images comparison is commonly performed by applying the log-ratio operator [11]. Sample feature vectors are 1-dimensional ($n = 1$) and the log-ratio image (lr) is defined as

$$lr = log\frac{b_1}{a_1} = logb_1 - loga_1. \tag{3}$$

In lr, unchanged pixels assume values around zero and changed pixels assume values far from zero.

B. Unsupervised Selection of the Pseudotraining Set (USPS)

The behaviors of change and no change classes are exploited in this step to define a pseudotraining set in an unsupervised way to be used as input for the next step of classification. The approach is based on unsupervised threshold selection [1], [13]. A threshold T is first computed that separates changed from unchanged pixel [1] according to the Bayes decision. The desired set of pixels with a high probability to be assigned to the class of change or no-changed is obtained by defining an uncertainty region around T that identifies highly uncertain pixels [13]. This region includes samples having magnitude in $[\mathrm{T} - \delta_1,\ \mathrm{T} + \delta_2]$. Samples showing magnitude larger than $\mathrm{T} + \delta_2$ have a high probability to be changed, whereas samples having magnitude smaller than $\mathrm{T} - \delta_1$ have a high probability to be unchanged. T is automatically estimated from the statistical distribution $p(d)$ of the magnitude image. A similar mechanism can be adopted for the analysis of lr. Fig. 4 gives an overview of the mechanism.

C. Concatenation and CSOM Classification (C^2SOM)

The third and fourth steps are the same as the ones in Section II-A. The unsupervised change detection is carried out by using the CSOM neural classifier [15], [22], [23], applied to concatenated vectors.

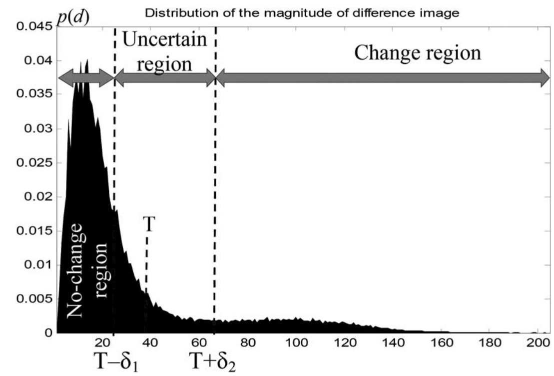


Fig. 4. Distribution p(d) of the samples in the SCV magnitude image d and relevant decision regions for pseudo-training set definition.

IV. Experiments and Results

A. Experimental Setup

The two approaches to change detection have been tested on three multitemporal datasets. In order to demonstrate its effectiveness results achieved with the proposed methods have been compared with ones obtained with: Bayes and NN statistical classifiers; MLP neural classifiers; and SVM with radial-basis function (RBF) kernel.

The Bayes (likelihood) classifier [1] performs decision according to

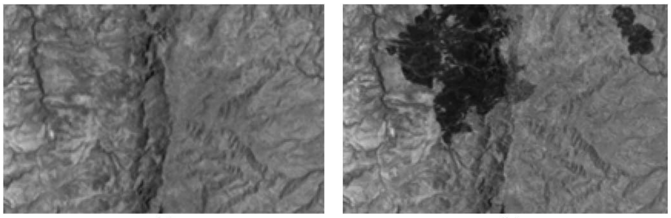
$$\begin{aligned}(X-\mu_{\mathrm{c}})^T \times {\textstyle\sum}_{\mathrm{c}}^{-1} \times (X-\mu_{\mathrm{c}}) - (X-\mu_{\mathrm{n}})^T \\ \times {\textstyle\sum}_{\mathrm{n}}^{-1} \times (X-\mu_{\mathrm{n}}) \\ + ln\frac{det\sum_{\mathrm{c}}}{det\sum_{\mathrm{n}}} \underset{>}{<} 2ln\frac{P(\omega_{\mathrm{c}})}{P(\omega_{\mathrm{n}})}\end{aligned} \tag{4}$$

where class conditional probability density functions have been implicitly considered as being Gaussian distributed. $\mu_{\mathrm{c}}, \mu_{\mathrm{n}}, \sum_{\mathrm{c}}$, $\sum_{\mathrm{n}}$, $\mathrm{P}(\omega_{\mathrm{c}})$, and $\mathrm{P}(\omega_{\mathrm{n}})$ are the average vectors, the covariance matrices, and the prior probabilities of change and no-change classes, respectively. All the above parameters are computed in a supervised way from the training set.

The NN classifier assigns the class by computing the distance from the input vector to each of the training vectors and by selecting the label of the NN.

MLP classifier is the standard neural network for pattern recognition tasks [24]. For change detection, an MLP configuration has been considered with $2n$ input neurons (one for each of the features in the concatenated vector) and 2 output neurons (one for change class and one *for no-change* class). Here an architecture with one hidden layer has been considered and the number of neurons in the hidden layer varied between 5 and 25. The learning rate was set to 0.01 and momentum constant to 0.9.

The RBF neural network has a three layer architecture similar to that of MLP [24]. Here, a Gaussian activation function for the hidden layer neurons has been considered. The RBF kernel spread parameter has been varied between 1 and 1000. Due to the nonlinearity of its hidden layer activation function, an RBF network can better approximate a desired pattern by comparison to MLP.



(a) (b)

Fig. 5. Band 4 of the Landsat-5 TM image on the Mexico area. (a) April 2000. (b) May 2002.

SVM is a supervised machine learning classifier based on a nonlinear mapping of the input vectors to a higher dimensional space [24]. The mapping is done based on a selected kernel function. For the present experiments, we have chosen a kernel based on RBF, namely a Gaussian function. Model selection has been performed according to a grid search strategy varying the spread between 0.001 and 100.

For the CSOM classifier, two neighborhood map lattices were considered: rectangular and hexagonal, combined with three different architectures: 1) sheet; 2) cylindrical; and 3) toroidal. The size range of SOM modules is from 2×2 till 25×25 neurons.

Change detection performance for the proposed methods and the reference one has been evaluated according to standard indexes. In greater detail missed alarms, false alarms and total errors have been computed in terms of number of pixels. In addition, the overall accuracy (OA), missing alarm rate (MAR), and false alarm rate (FAR) in percentage have been given for each trial. Finally, the Kappa accuracy is provided.

B. Mexico Dataset

1) Dataset Description: We have first experimented the proposed change detection techniques on the selection of 2 bands (namely 4 and 5) acquired by the Thematic Mapper (TM) sensor of the Landsat-5 satellite. The two images (512×360 pixels with 30 m resolution) were acquired in April 2000 and May 2002 [Fig. 5(a) and (b)] over a Mexico area [13]. Between the two acquisition dates a forest fire destroyed a large part of the forest. Reference map has been built by experts according to both in filed campaigns and accurate photointerpretation refinement. The burned area (29 506 pixels) represents the changed area in our dataset [coded with black color in Fig. 5(b)]. The remaining 154 814 pixels represent the unchanged area.

2) Results of the C^2SOM Supervised Change Detection Model for Mexico Dataset: We have used a selection of 2000 pixels for the training set, out of which 1000 are labeled as changed and 1000 as unchanged. These represent 1.09% of the total pixels. The remained 182 320 pixels (98.91%) are used for testing.

The first set of experiments aimed to compare CSOM classifier and reference classifiers taking into consideration their results in the best OA and MAR for the considered dataset. Also, the optimization of the CSOM architecture and size has been performed at this stage. Tables I–IV show the results.

The best results have been obtained by the proposed CSOM classifier, with a 97.73% OA and 1.64% miss alarm rate (MAR).

TABLE I
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CLASSIFIER TYPE (SUPERVISED APPROACH—MEXICO DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa Accuracy
		# pixels	%	# pixels	%			
1-NN	–	6095	3.96	1238	4.34	7333	95.98	0.857
Bayes	–	10 829	7.04	1730	6.07	12 559	93.11	0.769
MLP	1 hidden layer 12 neurons	3876	2.52	1300	4.56	5176	97.16	0.896
RBF	Spread = 31	3593	2.35	1518	5.14	5111	97.20	0.897
SVM-RBF	Spread = 5	3914	2.54	1274	4.47	5188	97.15	0.896
CSOM	**Hex sheet 20×8/16×3**	2640	1.72	1505	5.28	4145	**97.73**	**0.915**

TABLE II
BEST MAR AS A FUNCTION OF CLASSIFIER TYPE (SUPERVISED APPROACH—MEXICO DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	6095	3.96	1238	4.34	7333	95.98	0.857
Bayes	–	10 829	7.04	1730	6.07	12 559	93.11	0.769
MLP	1 hidden layer 5 neurons	4753	3.09	641	2.25	5394	97.04	0.894
RBF	Spread =10	5245	3.41	1457	5.11	6702	96.33	0.868
SVM-RBF	Spread = 5	3914	2.54	1274	4.47	5188	97.15	0.896
CSOM	**Rect Toroid 12×20/16×25**	7807	5.08	467	**1.64**	8274	95.46	0.844

TABLE III
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CSOM ARCHITECTURE ($MAR < 25\%$) (SUPERVISED APPROACH—MEXICO DATASET)

Topology	SOM1/SOM2	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. toroid	6×20/3×15	3449	2.24	1168	4.1	4617	97.47	0.907
Rect. sheet	12×5/7×3	2693	1.75	1686	5.91	4379	97.6	0.910
Rect. cylinder	11×8/12×3	2597	1.69	1675	5.88	4272	97.66	0.912
Hex. toroid	8×17/3×12	2920	1.9	1399	4.91	4319	97.63	0.912
Hex. sheet	**20×8/16×3**	2640	1.72	1505	5.28	4145	**97.73**	**0.915**
Hex. cylinder	16×5/13×3	2853	1.85	1513	5.31	4366	97.61	0.911

TABLE IV
BEST MAR AS A FUNCTION OF CSOM ARCHITECTURE ($OA > 80\%$) (SUPERVISED APPROACH-MEXICO DATASET)

Topology	SOM1/SOM2	False alarms		Missed alarms		Overall error	OA (%)	Kappa Accuracy
		# pixels	%	# pixels	%			
Rect. toroid	**12×20/16×25**	7807	5.08	467	**1.64**	8274	95.46	0.844
Rect. sheet	7×18/11×23	7582	4.93	543	1.9	8125	95.54	0.847
Rect. cylinder	6×20/13×25	7290	4.74	484	1.7	7774	95.74	0.853
Hex. toroid	19×17/24×22	7179	4.67	514	1.8	7693	95.78	0.854
Hex. sheet	18×20/21×25	5862	3.81	628	2.2	6490	96.44	0.874
Hex. cylinder	7×20/10×25	6703	4.36	508	1.78	7211	96.04	0.862

The optimum CSOM architecture has proved to be the hexagonal sheet with modules of $20 \times 8/16 \times 3$, maximizing both OA and Kappa. The best (minimum) MAR is obtained using a rectangular toroid with module sizes of $12 \times 20/16 \times 25$.

The best benchmark classifiers reach OA less than the CSOM performance (97.73%), namely, between 97.15% for SVM, 97.16% for MLP, and 97.20% for RBF. For the MAR, the advantage of CSOM over the benchmark classifiers is more significant, the NN of CSOM being MLP with 2.25% (by comparison to 1.64% for CSOM).

We have also considered the evolution of the OA and MAR scores for various SOM module sizes, to deduce a potential correlation. Figs. 6 and 7 display the evolution of the two performance indicators for square SOM modules, in the size range from 5×5 to 20×20 neurons. By increasing the SOM size, one obtains a better OA and a better MAR.

One can remark that CSOM leads also to the best Kappa accuracy of 0.915.

Fig. 8 shows as an example the change detection map obtained by using the CSOM classifier that resulted in the best OA.

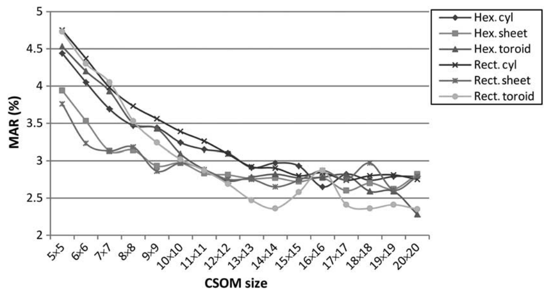


Fig. 6. MAR for different CSOM architectures as a function of SOM module size (supervised approach—Mexico dataset) (lower is better).

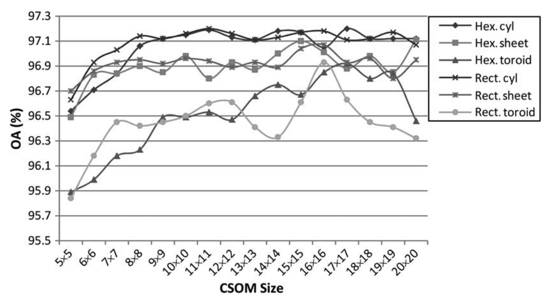
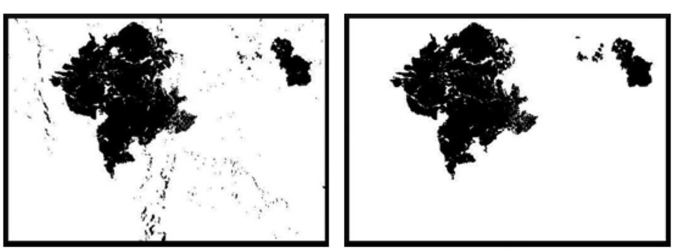


Fig. 7. Overall accuracy (OA) for different CSOM architectures (supervised approach—Mexico dataset).



(a) (b)

Fig. 8. (a) Change detection map obtained by the supervised approach for Mexico dataset using CSOM (hexagonal sheet with module sizes $20 \times 8/16 \times 3$). (b) Reference map (black pixels are changed; white pixels are unchanged).

3) Results of the IC-USPS—C^2SOM Unsupervised Change Detection Model for Mexico Dataset: The unsupervised selection of the pseudotraining set (USPS) selected 19 798 changed pixels, 106 484 unchanged pixels, and 58 038 unlabeled pixels. The selected changed and unchanged pixels represent the pseudotraining set. The test set contains all the image pixels, labeled according to the truth reference map.

The experimental results of the proposed unsupervised approach for change detection are given in Tables V–VIII. The change map obtained by the best classifier (CSOM with symmetrical rectangular cylinder modules of 12×12) is shown in Fig. 9.

From Tables V and VI, one can deduce that CSOM leads to best performances by comparison to the considered benchmark classifiers. The best OA result of 97.78% and the best Kappa accuracy of 0.917 have been obtained for a CSOM classifier (Table V). The best missed alarm rate of 3.83% (Table VI)

TABLE V
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CLASSIFIER TYPE (UNSUPERVISED APPROACH—MEXICO DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	3074	1.98	3840	13.01	6914	96.24	0.859
Bayes	–	3716	2.40	1489	5.04	5205	97.18	0.898
MLP	1 hidden layer 8 neurons	2064	1.33	3117	10.56	5181	97.18	0.893
RBF	Spread = 150	1972	1.27	2279	7.72	4251	97.69	0.913
SVM-RBF	Spread = 0.01	1128	0.72	3811	12.91	4939	97.32	0.896
CSOM	**Rectcyl 11×19/11×19**	2042	1.31	2042	6.92	4084	**97.78**	**0.917**

TABLE VI
BEST MISSED ALARM RATE (MAR) AS A FUNCTION OF CLASSIFIER TYPE (UNSUPERVISED APPROACH—MEXICO DATASET)

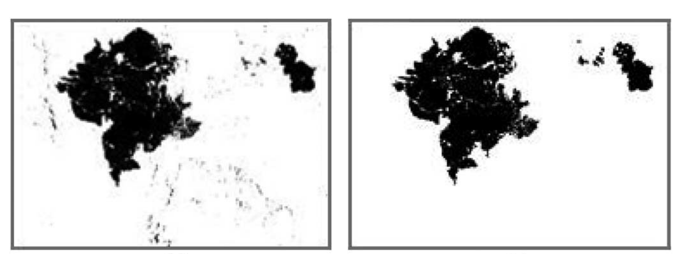
Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	3074	1.98	3840	13.01	6914	96.24	0.859
Bayes	–	3716	2.40	1489	5.04	5205	97.18	0.898
MLP	1 hidden layer 6 neurons	4981	3.21	1790	6.06	6771	96.32	0.869
RBF	Spread = 150	1972	1.27	2279	7.72	4251	97.69	0.913
SVM-RBF	Spread = 0.05	1272	0.82	3803	12.88	5075	97.24	0.893
CSOM	**Rect toroid 25×25/25×25**	4965	3.20	1131	**3.83**	6096	96.69	0.883

TABLE VII
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CSOM TOPOLOGY ($MAR < 25\%$) (UNSUPERVISED APPROACH—MEXICO DATASET)

Topology	Symmetrical SOM module size	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. sheet	11×21	2328	1.50	1798	6.09	4126	97.76	0.917
Hex. sheet	11×19	2433	1.57	1713	5.80	4146	97.75	0.917
Rect. cylindrical	**11×19**	2042	1.31	2042	6.92	4084	**97.78**	**0.917**
Hex. cylindrical	13×25	2288	1.47	1853	6.28	4141	97.75	0.916
Rect. toroidal	15×24	3399	2.19	1468	4.97	4867	97.35	0.904
Hex. toroidal	17×21	3312	2.13	1489	5.04	4801	97.39	0.905

TABLE VIII
BEST MISSED ALARM RATE (MAR) AS A FUNCTION OF CSOM TOPOLOGY ($OA > 80\%$) (UNSUPERVISED APPROACH—MEXICO DATASET)

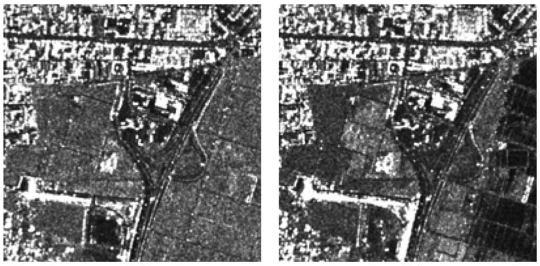
Topology	Symmetrical SOM module size	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. sheet	11×25	2624	1.69	1631	5.52	4255	97.69	0.915
Hex. sheet	11×21	2459	1.58	1699	5.75	4158	97.74	0.916
Rect. cylindrical	11×25	2286	1.47	1863	6.31	4149	97.74	0.916
Hex. cylindrical	11×25	2673	1.72	1681	5.69	4354	97.63	0.913
Rect. toroidal	**25×25**	4965	3.20	1131	**3.83**	6096	96.69	0.883
Hex. toroidal	11×25	4106	2.65	1323	4.48	5429	97.05	0.894



(a) (b)

Fig. 9. (a) Change detection map obtained by the unsupervised approach for Mexico dataset using CSOM (rectangular–cylindrical modules of sizes $12 \times 12/12 \times 12$). (b) Reference map (black pixels are changed; white pixels are unchanged).

corresponds also to CSOM classifier. Tables VII and VIII give the best performances (OA and, respectively, MAR) as a functions of CSOM module architecture and neighborhood lattice. The best OA is obtained using a CSOM architecture corresponding to a rectangular-cylindrical topology with symmetrical



(a) (b)

Fig. 10. Fukushima TerraSAR-X image sequence. (a) March 2009. (b) May 2011.

TABLE IX
BEST OVERALL ACCURACY (OA), AS A FUNCTION OF CLASSIFIER TYPE (SUPERVISED APPROACH—FUKUSHIMA DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	15 269	13.68	18 639	40.27	15 269	78.53	0.471
Bayes	–	28 071	25.15	8331	18	28 071	76.94	0.506
MLP	1 hidden layer 9 neurons	8516	7.63	13 751	29.71	8516	85.9	0.648
RBF	Spread = 100	8550	7.66	14 126	30.52	8550	85.64	0.641
SVM-RBF	spread = 0.001	8603	7.7	13 900	30.03	22 503	85.76	0.639
CSOM	**Rect sheet 5×7/3×7**	7981	7.15	8470	18.3	7981	**89.58**	**0.748**

TABLE X
BEST MAR AS A FUNCTION OF CLASSIFIER TYPE (SUPERVISED APPROACH—FUKUSHIMA DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	15 269	13.68	18 639	40.27	33 908	78.53	0.471
Bayes	–	28 071	25.15	8331	18	36 402	76.94	0.506
MLP	1 hidden layer 10 neurons	11 709	10.49	11 423	24.68	23 132	85.35	0.647
RBF	Spread = 64	10 079	9.03	13 316	28.77	23 395	85.18	0.635
SVM-RBF	Spread = 0.004	8945	8.01	13 595	29.37	22 540	85.73	0.640
CSOM	**Rect sheet 5×8/10×10**	28 462	25.5	2647	**5.72**	31 109	80.3	0.591

modules of sizes 11×19. The best (minimum) MAR is obtained using a rectangular lattice and toroidal architecture with symmetrical modules of sizes 25×25.

C. Fukushima Dataset

1) Fukushima Dataset Description: The second dataset is composed of two 400×400 pixel radar brightness images (StripMap imaging mode, up to 3 m resolution) acquired by TSX-1 sensor of TerraSAR-X Earth Observation satellite over the Fukushima region in Japan [Fig. 10(a) and (b)]. The first image is from March 2009, while the second is from May 2011. The region was hit by a tsunami in March 2011, which caused drastic modifications to the landscape. The dataset contains 46 836 pixels of change ($\sim 29.27\%$) and 113 164 pixels of unchanged ($\sim 70.73\%$), the reference map being labeled by experts using a photointerpretation method.

2) Results of the C^2SOM Supervised Change Detection Model for Fukushima Dataset: Similar to the Mexico dataset, we have used a selection of 2000 pixels (1.25% of the total) for the training set, 552 labeled as change ($\sim 27.6\%$ of the training set) and 1448 labels as no-change ($\sim 72.4\%$ of the training set). The rest of 158 000 pixels (98.75%) are used for testing.

TABLE XI
BEST TOTAL OVERALL ACCURACY (OA) AS A FUNCTION OF CSOM ARCHITECTURE ($\mathrm{MAR} < 25\%$) (SUPERVISED APPROACH—FUKUSHIMA DATASET)

Topology	SOM1/SOM2	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. toroid	6×5/4×6	9175	8.22	7628	16.48	16 803	89.36	0.746
Rect. sheet	**5×7/3×7**	7981	7.15	8470	18.3	16 451	**89.58**	**0.748**
Rect. cylinder	7×5/4×7	8818	7.90	8512	18.39	17 330	89.02	0.736
Hex. toroid	7×5/5×5	8829	7.91	8401	18.15	17 230	89.09	0.737
Hex. sheet	5×6/4×5	8126	7.28	8493	18.35	16 619	89.48	0.745
Hex. cylinder	8×5/4×5	7813	7.00	9650	20.85	17 463	88.94	0.730

TABLE XII
BEST MAR AS A FUNCTION OF CSOM ARCHITECTURE ($\mathrm{OA} > 80\%$) (SUPERVISED APPROACH—FUKUSHIMA DATASET)

Topology	SOM1/SOM2	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. toroid	5×5/6×8	26 486	23.73	3818	8.25	30 304	80.80	0.595
Rect. sheet	**5×8/10×10**	28 462	25.5	2647	**5.72**	31 109	80.30	0.591
Rect. cylinder	5×12/10×14	27 357	24.51	2995	6.47	30 352	80.78	0.598
Hex. toroid	5×5/6×8	24 377	21.84	3606	7.79	27 983	82.27	0.622
Hex. sheet	5×5/9×7	28 618	25.64	2754	5.95	31 372	80.13	0.588
Hex. cylinder	5×8/10×11	25 649	22.98	3101	6.7	28 750	81.79	0.616

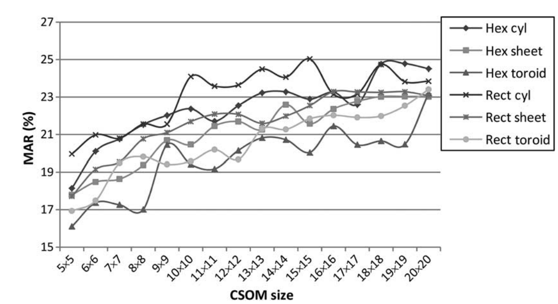


Fig. 11. MAR for different CSOM architectures as a function of SOM module size (Supervised approach—Fukushima dataset) (lower is better).

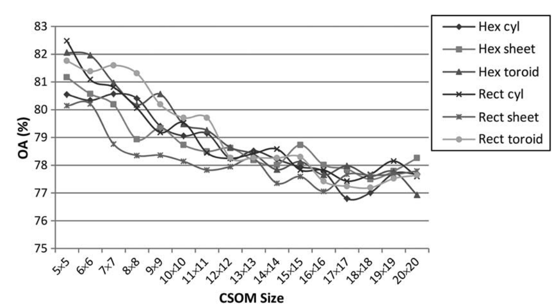


Fig. 12. Overall accuracy (OA) for different CSOM architectures (supervised approach—Fukushima dataset).

Tables IX–XII and Figs. 11–13 show the results obtained by applying the $\mathrm{C}^2\mathrm{SOM}$ supervised model on the Fukushima SAR dataset. The results confirm the advantage of the CSOM classifier for change detection.

From Tables IX and X, one can deduce that CSOM classifier maximizes OA (89.58%) and Kappa accuracy (0.748) for a rectangular sheet topology of module sizes $5 \times 7/3 \times 7$. From Tables X and XII, one can remark that CSOM also minimizes MAR (5.72%), for CSOM modules of rectangular sheet with sizes $5 \times 8/10 \times 10$.

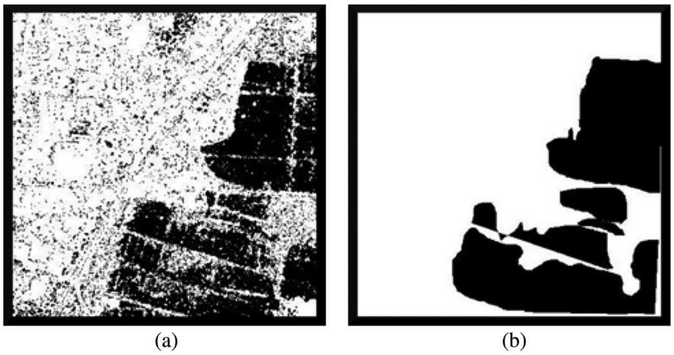


Fig. 13. (a) Change detection map obtained by the supervised approach with Fukushima dataset using CSOM (rectangular sheet with $5 \times 7/3 \times 7$ size). (b) Reference change detection map (black pixels are changed; white pixels are unchanged).

TABLE XIII
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CLASSIFIER TYPE (UNSUPERVISED APPROACH—FUKUSHIMA DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	13 683	12.09	12 121	25.87	25 804	83.87	0.614
Bayes	–	14 601	12.90	11 654	24.88	26 255	83.59	0.610
MLP	1 hidden layer 15 neurons	14 559	12.86	11 686	24.95	26 245	83.59	0.610
RBF	Spread = 200	13 095	11.57	13 202	28.18	26 297	83.56	0.602
SVM-RBF	Spread = 0.001	12 449	11.00	13 203	28.18	25 652	83.96	0.611
CSOM	**Hex sheet 6×16/6×16**	**14 555**	**12.86**	**10 736**	**22.92**	**25 291**	**84.19**	**0.627**

TABLE XIV
BEST MISSED ALARM RATE (MAR) AS A FUNCTION OF CLASSIFIER TYPE (UNSUPERVISED APPROACH—FUKUSHIMA DATASET)

Classifier	Parameters	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
1-NN	–	13 683	12.09	12 121	25.87	25 804	83.87	0.614
Bayes	–	14 601	12.90	11 654	24.88	26 255	83.59	0.610
MLP	1 hidden layer 10 neurons	14 601	12.90	11 654	24.88	26 255	83.59	0.610
RBF	Spread = 300	21 546	19.03	11 724	25.03	33 270	79.20	0.526
SVM-RBF	Spread = 10	14 576	12.88	11 670	24.91	26 246	83.59	0.610
CSOM	**Recttoroidal 6×12/6×12**	20 345	17.97	9399	**20.06**	29 744	81.41	0.579

Figs. 11 and 12 display the evolution of the OA and MAR indicators for square SOM modules, in the size range from 5×5 to 20×20 neurons.

Fig. 13 shows the change detection map obtained by using the CSOM classifier that resulted in the best overall/Kappa accuracy.

3) Results of the IC-USPS—C^2SOM Unsupervised Change Detection Model for Fukushima SAR Dataset: As a result of unsupervised selection of the pseudotraining set (USP), one obtains 42 281 changed pixels, 93 719 unchanged pixels, and 24 000 unlabeled pixels. The test set contains all the image pixels, visually labeled to generate a kind of reference map.

The experimental results of the proposed unsupervised approach are given in Tables XIII–XVI. The change map obtained by the best classifier (CSOM with symmetrical hexa sheet modules of 6×18 neurons) is shown in Fig. 14.

From Tables XIII–XVI, one can deduce that CSOM leads to best performances by comparison to the considered benchmark classifiers. The best OA result of 84.19% and the best Kappa accuracy of 0.627 have been obtained for CSOM classifier (Table XIII). The best missed alarm rate of 20.06% (Table XIV) corresponds also to the CSOM classifier. Tables XV and XVI give the best performances (OA and, respectively, MAR) as a functions of CSOM module architecture and neighborhood lattice. The best OA is obtained using a CSOM architecture corresponding to a hexagonal sheet topology with symmetrical modules of size 6×16. The minimum MAR is obtained using a rectangular-toroidal architecture with symmetrical modules of sizes 6×12.

TABLE XV
BEST OVERALL ACCURACY (OA) AS A FUNCTION OF CSOM TOPOLOGY ($\text{MAR} < 25\%$) (UNSUPERVISED APPROACH—FUKUSHIMA DATASET)

Topology	Symmetrical SOM module size	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. sheet	6×14	14 778	13.05	10 679	22.80	25 457	84.08	0.625
Hex. sheet	**6×16**	14 555	12.86	10 736	22.92	25 291	**84.19**	0.627
Rect. cylindrical	6×10	14 926	13.18	10 900	23.27	25 826	83.85	0.619
Hex. cylindrical	6×14	15 016	13.26	10 702	22.84	25 718	83.92	0.622
Rect. toroidal	6×6	16 567	14.63	10 213	21.80	26 780	83.26	0.611
Hex. toroidal	8×8	15 750	13.91	10 224	21.82	25 974	83.76	0.621

TABLE XVI
BEST MISSED ALARM RATE (MAR) AS A FUNCTION OF CSOM TOPOLOGY ($\text{OA} > 80\%$) (UNSUPERVISED APPROACH-FUKUSHIMA DATASET)

Topology	Symmetrical SOM module size	False alarms		Missed alarms		Overall error	OA (%)	Kappa accuracy
		# pixels	%	# pixels	%			
Rect. sheet	4×4	17 195	15.19	10 081	21.52	27 276	82.95	0.605
Hex. sheet	4×4	18 363	16.22	9850	21.03	28 213	82.36	0.595
Rect. cylindrical	6×10	14 926	13.18	10 900	23.27	25 826	83.85	0.619
Hex. cylindrical	6×18	16 781	14.82	10 170	21.71	26 951	83.15	0.609
Rect. toroidal	**6×12**	20 345	17.97	9399	**20.06**	29 744	81.41	0.579
Hex. toroidal	6×6	16 965	14.99	10 025	21.40	26 990	83.13	0.609

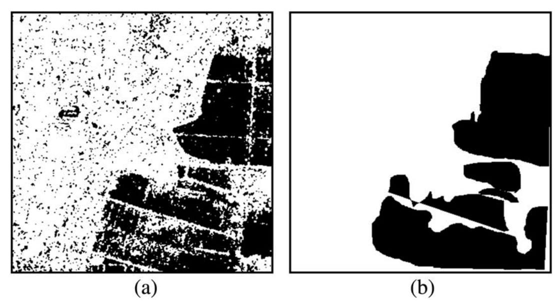


Fig. 14. (a) Change-detection map obtained by the unsupervised approach with the Fukushima dataset by using CSOM (hexagonal sheet symmetrical modules of 6×16 neurons). (b) Reference map (black pixels are changed; white pixels are unchanged).

V. CONCLUDING REMARKS

This paper addresses a problem of high interest with large applications in Geomonitoring, namely change detection in remote sensing mutitemporal images. The novelty of the paper consists in extending the use of CSOM classifier to change detection. Two CSOM-based approaches have been proposed, one for supervised and one for unsupervised change detection. The methods have been validated on two datasets, first one being obtained by a passive sensor (TM of LANDSAT-5) and the second dataset being acquired by an active sensor (TSX-1 of TerraSAR-X).

Experimental results confirm the effectiveness of the CSOM-based supervised/unsupervised change detection methods when compared with standard MLP-NN, RBF-NN, and SVM in terms of OA, Kappa accuracy, and error rate.

As future work direction, we prepare a fully neural model for unsupervised change detection, by substituting the Bayes-ME stage of the pseudotraining set selection with a neural technique.

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Deep Convolutional Neural Networks versus Multilayer Perceptron for Financial Prediction

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***Abstract*—This paper presents a new approach to apply and evaluate Deep Learning (DL) Convolutional Neural Networks (CNN) versus Multilayer Perceptron (MLP) for financial prediction. We have designed and evaluated a credit scoring model based on neural network classifiers in two variants: (a) MLP with eight layers; (b) DCNN with thirteen layers (six main layers and seven secondary layers). The experiments have used the German credit dataset and the Australian credit dataset. The model performances are evaluated by the following indices: Overall Accuracy (OA); False Alarm Rate (FAR); Missed Alarm Rate (MAR). The experimental results have confirmed the effectiveness of the proposed approach, pointing out the significant advantage of DCNN over the MLP. For German credit dataset, the DCNN leads to the best OA of 90.85%, versus the corresponding best MLP performance of only 81.20%. For Australian credit dataset, the DCNN has led to the best OA of 99.74%, while the MLP has obtained the best corresponding OA of 90.75%.**

Keywords—financial prediction, credit scoring, Multilayer Perceptron (MLP); Deep Learning (DL); Convolutional Neural Networks (CNN)

I. INTRODUCTION

The banks are aware of various risks [1], [2], [3]. As a consequence, the bank has to analyze the corresponding risk factors in order to optimize its decisions. The capacity to predict business failure is crucial, since incorrect decisions can lead to direct financial consequences. Credit scoring focusing on credit admission evaluation represents a serious task for financial institutions [1], [2], [3], [4]. A credit scoring model has as aim to decide whether to grant a credit to a client, taking into account the customer's features, such as income, age, marital status, education, employment status, number of existing credits, and so on.

The introduction of modern technologies has made significant changes in bank business [2]. Machine learning and data mining classifiers are used with success for financial models [1], [2], [3], [4], [5], [6], [7], [8], [9]. The stage of learning (training) consists of computation of the model parameters that approximate the mapping between input-output examples given by the labeled training set. After model learning, it can classify an unknown input sample [8], [9]. A multilayer perceptron (MLP) is a feedforward artificial neural network containing at least three layers of neurons (input layer, hidden layer, and output layer). Except for the input neurons, each neural unit uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training [8], [9], [10], [11]. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can recognize data that is not linearly separable [8], [9], [10], [11].

The solution of many artificial intelligence (AI) classification tasks depends on designing an appropriate set of features to be extracted [12]. One solution for this difficult problem is to use machine learning not only to solve the mapping from input representation to output but to discover the representation itself. This approach is named representation learning [12]. It allows AI systems to fast adaptation for new tasks with a minimum of human intervention. Representation learning leads to much better performance; it can faster discover a good set of features from raw data. Deep learning (DL) solves the problem of representation learning by the introduction of the representations that are expressed in terms of other, simpler representations [12], [13]. DL is a kind of machine learning that improves the computer with experience and data [12]. From some point of view, a DL architecture can be considered as a deeper extension of the MLP. Depth allows the computer to learn a multi-step program. Convolutional Neural Networks (CNN) are a special kind of DL feed-forward neural networks characterized by a grid-like topology and by the property of using convolution in at least one of their layers [12], [13]. A typical CNN involves four types of layers: convolutional, activation, pooling and fully-connected (dense) layers.

Within this paper we propose a neural network classifier model for credit scoring in two variants. First method uses a MLP with eight layers (input layer; six hidden layers; output layer). Second method is based on the DCNN architecture with six main layers: (input layer, three long short-term memory layers, and two fully connected layers) and other seven secondary layers (four dropout layers, Relu layer, softmax layer, and classification layer). For experimental evaluation of the proposed model, we have used two publicly downloadable datasets: German credit dataset (1000 two-class data in numerical form with 25 features each, including class label) [14], and also the Australian credit card assessment dataset (690 two-class data with 15 features each, including binary class label) [15].

II. PROPOSED NEURAL NETWORK CLASSIFIER MODEL FOR CREDIT SCORING

We further present two variant of the proposed credit scoring model, using two class supervised classification of customer feature vectors corresponding to the labels “good” or “bad”.

A. Multilayer Perceptron (MLP) Classifier for Credit Scoring

We have chosen an architecture of maximum eight layers MLP:

– input layer with ***m*** neurons, where m is the number of customer’s features

– H hidden layers with ***NH*** neurons each of them (max(H)=6)

– output layer with two neurons (corresponding to the decisions “good” and “bad”).

We propose to perform MLP training with Broyden-Fletcher-Goldfarb-Shannon (BFGS) quasi-Newton algorithm [16], that has proved to lead to significantly better performances than those obtained by classical Levenberg-Marquardt backpropagation [11].

B. Deep Convolutional Neural Networks (DCNN) Classifier for Credit Scoring

We propose a credit scoring classifier architecture composed by the following thirteen DCNN layers:

• *input* layer with ***m*** neurons (corresponding to the number of client’s features);

• *three main layers* of the kind *Long Short-Term Memory (LSTM),* from layer 2 to layer 4, with ***N*** neurons each of them, each of the above main layers being associated with a corresponding secondary *dropout layer* with the probability D.

• Fully Connected (FC) layer (main layer number 5) with N neurons, the FC layer being associated with two secondary layers:

– *Dropout layer* with the probability D

– *Relu layer*

• Fully Connected (FC) layer (main layer number 6) with two neurons, the FC layer being associated with two secondary layers:

– *Softmax layer*

– *Classification layer*

Inclusion of the dropout layers is a consequence of the regularization approach used to reduce the overfitting.

We have chosen the Stochastic Gradient Descent with Momentum for DCNN training.

III. EXPERIMENTS AND RESULTS

A. Experimental Setup

We have evaluated the credit scoring performances according to the proposed model in terms of the indicators defined below {Overall Accuracy (OA), Miss Alarm Rate (MAR) and False Alarm Rate (FAR)}

Denote:

– TP (True Positives) = number of test data correctly classified as “bad”;

– TN (True Negatives) = number of test data correctly classified as “good”;

– FP (False Positives) = number of test data incorrect classified as “bad”.

– FN (False Negatives) = number of test data incorrect classified as “good”.

– NT=TP+TN+FP+FN=total number of test data

Define:

– False Alarm Rate (FAR) (%)

$$FAR = FP/(FP+TN)\times 100\ [\%] \qquad (1)$$

– Miss Alarm Rate (MAR) (%):

$$MAR = FN/(FN+TP)\times 100\ [\%] \qquad (2)$$

– Overall Accuracy (OA) (%):

$$OA = (TP+TN)/\ N_T \times 100\ [\%] \qquad (3)$$

B. German Credit Dataset

- *Dataset Description*

We have firstly considered the German credit dataset provided by Strathclyde University in the variant of numerical attributes, included in the file “German.data-numeric” [14]. The considered dataset (numerical variant) is composed by 1000 vectors (data) with 25 features each, including customer label (1=good; 2=bad). The other **m=24** customer’s features correspond to the numerical encoding of the characteristics as: age, income, employment, marital status and sex, properties (house, car), qualifications (skills); existing credits, and so on.

- *Experimental Results*

The experimental results for German dataset are given in Tables I, II and III. We have chosen the OA performance (yellow column) as a main target.

In Table I, one can evaluate MLP credit scoring performances. One deduces that by increasing the number of hidden layers, the OA is improved. The best OA performance of 81.20 % corresponds to the maximum of H=6 hidden layers. One can also remark, that the best performance (for a given number of H layers) corresponds to choose the number of hidden neurons in the interval [12, 18].

Table II shows that choosing a MLP architecture with all the six hidden layers, the OA performance does not usually depend too much on the number of neurons NH characterizing each hidden layer.

Table III shows better performances of DCNN classifier for credit scoring, taking the MLP as a reference. We have marked by red color the cases with OA over 90%.

By increasing the number N of neurons of each of the main layers {2,3,4,5}, one remarks a general increasing of performances and the increasing of the number of cases with OA greater than 90%.

The best performance regarding OA is of 90.85% and this corresponds to choose a number of N=296 neurons for each layer.

By considering only the cases with OA greater than 90%, the best MAR (lower is better) is of 3.81%, and it corresponds to N=362.

TABLE I. BEST MLP CREDIT SCORING OVERALL ACCURACY (OA) AS A FUNCTION OF THE NUMBER OF HIDDEN LAYERS (GERMAN CREDIT DATASET) (MLP TRAINING WITH BFGS QUASI-NEWTON ALGORITHM; **NL=500** TRAINING DATA; **NT=250** TEST DATA)

Number of hidden layers (H)	Number of neurons of any hidden layer for best OA (NH)	Overall Accuracy (OA) [%]	False Alarm (FAR) [%]	Missed Alarm (MAR) [%]
1	16	78.40	14.12	39.73
2	16	76.80	18.46	40
3	12	77.60	17.13	36.23
4	14	78.40	19.81	30.23
5	18	77.60	18.96	41.03
6	**18**	**81.20**	13.98	32.81

TABLE II. MLP CREDIT SCORING OVERALL ACCURACY (OA) AS A FUNCTION OF THE NUMBER OF NEURONS FOR EACH OF THE HIDDEN LAYERS (GERMAN CREDIT DATASET; MLP TRAINING WITH BFGS QUASI-NEWTON ALGORITHM; **NL=500** TRAINING DATA**; NV= 250** VALIDATION DATA; **NT**=250 TEST DATA; H=6 HIDDEN LAYERS)

Number of neurons of any hidden layer for best OA (NH)	Overall accuracy (OA) for training set [%]	Overall accuracy (OA) for validation set [%]	Overall Accuracy (OA) for test set [%]	Overall Accuracy (OA) for all data [%]
1	73.20	70.40	68.80	71.40
2	72.80	67,20	70.80	70.90
4	77.00	72.80	72.00	74.70
6	76.20	72.40	73.20	74.50
8	79.40	71.20	77.60	76.90
10	76.60	70.80	74.80	74.70
12	81.40	72.80	72.00	76.90
14	82.40	70.80	72,.40	7.00
16	76.00	75.60	71.20	74.70
18	78.40	75.20	**81.20**	78.30
20	79.20	75.60	70.80	76.20
22	79.20	75.60	70.80	76.20

TABLE III. DCNN CREDIT SCORING PERFORMANCES AS A FUNCTION OF THE NUMBER OF NEURONS FOR EACH OF THE MAIN LAYERS {2,3,4,5} (GERMAN CREDIT DATASET; DCNN TRAINING USING THE ALGORITHM OF STOCHASTIC GRADIENT DESCENT WITH MOMENTUM; **NL=300** TRAINING DATA; **NT**=700 TEST DATA)

Number of neurons N of each of layers {2,3,4,5}	Overall Accuracy (OA) [%]	False Alarm (FAR) [%]	Missed Alarm (MAR) [%]
130	86.42	30.00	9.00
142	83.42	53.33	6.54
155	87.14	33.33	7.27
158	**90.00**	**18.66**	**7.63**
162	86.85	20.00	11.27
167	85.28	25.33	11.81
177	84.28	8.66	17.63
181	87.42	9.33	13.45
190	88.42	28.66	6.90
194	85.57	16.66	13.81
203	87.71	32.66	6.72
204	88.14	20	9.63
212	88.42	21.33	8.90
217	87.42	18.00	11.09
223	88.42	18.66	9.63
234	87.28	17.33	11.45
237	**90.57**	**16.66**	**7.45**
250	89.42	22.00	7.45
257	89.42	17.33	8.72
284	87.14	2.00	15.81
286	**90.28**	**17.33**	**7.63**
293	**88.28**	**23.33**	**8.54**
296	**90.85**	**32.00**	**2.90**
304	89.14	5.33	12.36
313	89.42	5.33	12.00
320	**90.00**	**5.333**	**11.27**
328	89.14	20.66	7.45
331	88.28	2.66	14.18
348	**90.14**	**20.66**	**6.90**
357	87.57	8.667	13.45
361	**90.14**	**19.33**	**7.27**
362	**90.14**	**32.00**	**3.81**
376	89.42	34.00	4.18
379	**90.42**	**18.66**	**7.09**
382	89.85	18.66	7.81
387	**90.14**	**16.66**	**8.00**
392	87.57	7.33	13.81
394	**90.14**	**20.00**	**7.09**
396	89.57	15.33	9.09
399	**90.28**	**18.66**	**7.27**

C. Australian Credit Dataset

- *Dataset Description*

We have also considered the Australian credit card assessment dataset [15], containing 690 patterns (vectors) with **m=14** attributes; 6 numeric and 8 discrete (with 2 to 14 possible values). The 15th feature is the binary class label.

- *Experimental Results*

The experimental results for Australian credit approval dataset are given in Tables IV and V.

Table IV shows that the OA performance of Australian credit dataset for a MLP with eight layers is not influenced too much by the number of hidden neurons. The best OA of 90.75 % is obtained for NH=41 neurons. By considering only cases with OA bigger than 89%, one can deduce that the best (minimum) MAR is of 8.64% and it is obtained by choosing NH=22 neurons.

Table V shows the very good performances of DCNN classifier for credit scoring, significantly higher than those obtained by MLP. We have marked by red color the cases with OA over 99%.

By choosing the number N of neurons of the main layers {2,3,4,5} in the interval [65, 129], we have obtained a stable behavior of the proposed DCNN architecture, with a significant number of cases with OA higher than 99%. The best OA of 99.74% is obtained for N=85 and N=98; for the same two higher performance cases, one obtains MAR of 0% and FAR of 0.63%.

TABLE IV. MLP CREDIT SCORING PERFORMANCES FOR THE AUSTRALIAN CREDIT APPROVAL **TEST** DATASET AS A FUNCTION OF THE NUMBER OF NEURONS FOR EACH OF THE HIDDEN LAYERS (MLP TRAINING WITH BFGS QUASI-NEWTON ALGORITHM; **NL=344** TRAINING DATA**; NT=173** TEST DATA; H=6 HIDDEN LAYERS)

Number of neurons of any hidden layer for best OA (NH)	Overall Accuracy (OA) [%]	False Alarm (FAR) [%]	Missed Alarm (MAR) [%]
1	87.86	12.12	12.16
2	88.44	2.63	18.56
3	83.82	14.00	19.18
4	86.13	11.88	16.67
5	89.02	4.65	17.24
6	87.86	8,70	16.05
7	87.86	16.33	6.67
8	81.50	11.70	26.58
9	87.28	13.13	12.16
10	83.82	12.24	21.33
11	88.44	8.64	14.13
12	86.13	11.43	17.65
13	87.86	10.99	13.41
14	77.46	20.51	24.21
15	87.28	9.09	16.47
16	83.24	10.42	24.68
17	83.24	20,00	12.82
18	87.28	7.61	18.52
19	86.13	10.59	17.05
20	81.50	19.79	16.88
21	86.13	16.83	9.72
22	89.60	**11.96**	**8.64**
23	88.44	14.13	8.64
24	89.02	**7.14**	**16.00**
25	79.77	15.24	27.94
26	84.39	15.91	15.29
27	84.97	16.48	13.41
28	87.86	12.35	11.96
29	87.86	10.99	13.41
30	84.39	13.48	17.86
31	84.39	13.33	18.07
32	84.97	11.32	20.90
33	83.24	12.50	22.08
34	89.02	**10.47**	**11.49**
35	81.50	11.83	26.25
36	86.71	10.47	16.09
37	84.97	16.50	12.86
38	82.66	9.20	25.58
39	83.82	13.73	19.72
40	83.24	9.78	24.69
41	90.75	**8.91**	**9.72**
42	87.86	8.70	16.05
43	83.82	11.90	20.22
44	85.55	10.59	18.18
45	87.28	12.38	13.24

TABLE V. DCNN CREDIT SCORING PERFORMANCES AS A FUNCTION OF THE NUMBER OF NEURONS FOR EACH OF THE LAYERS {2,3,4,5} (AUSTRALIAN CREDIT APPROVAL DATASET; DCNN TRAINING USING THE ALGORITHM OF STOCHASTIC GRADIENT DESCENT WITH MOMENTUM; **N_L=300** TRAINING DATA (150 CREDIT APPROVAL +150 CREDIT REJECTION) ; **N_T=390** TEST DATA)

Number of neurons N of each of main layers {2,3,4,5}	Overall Accuracy (OA) [%]	False Alarm (FAR) [%)]	Missed Alarm (MAR) [%]
64	95.64	0	7.29
65	**99.23**	**1.91**	**0**
66	92.82	0	12.01
67	98.72	3.18	0
68	95.64	3.18	5.15
69	96.41	0	6.00
70	**99.23**	**1.91**	**0**
71	98.97	2.54	0
72	93.33	16.56	0
73	94.36	0	9.44
74	92.82	0	12.01
75	93.59	0	10.72
76	**99.23**	**0.63**	**0.85**
77	**99.49**	**0.63**	**0.42**
78	**99.23**	**1.91**	**0**
79	**99.49**	**0.63**	**0.42**
80	**99.49**	**1.27**	**0**
81	**99.23**	**1.91**	**0**
82	98.72	**0**	**2.14**
83	**99.23**	**1.91**	**0**
84	**99.23**	**1.27**	**0.42**
85	**99.74**	**0.63**	**0**
86	98.72	0	2.14
87	98.72	1.27	1.28
88	**99.23**	1.91	0
89	98.97	1.91	0.42
90	98.72	3.18	0
91	**99.23**	**0.63**	**0.85**
92	**99.23**	**1.91**	**0**
93	**99.23**	**1.27**	**0.42**
94	**99.23**	**1.91**	**0**
95	**99.23**	**1.91**	**0**
96	98.97	2,54	0
97	95.13	0	8.15
98	**99.74**	**0.63**	**0**
99	97.69	5.09	0.42
100	98.97	2.54	0

IV. CONCLUDING REMARKS

This paper proposes a new neural network classifier model for financial prediction in two variants. First variant uses a MLP with eight layers trained with Broyden-Fletcher-Goldfarb-Shannon (BFGS) quasi-Newton algorithm. Second variant implies a DCNN architecture with thirteen layers (six main layers and seven secondary layers), using a Stochastic Gradient Descent with Momentum algorithm for training.

The experimental results have confirmed the effectiveness of the proposed approach. The performance difference between the two variants is significant; one can clearly point out the important advantage of DCNN over the MLP.

For the German credit dataset, the DCNN leads to the best OA of 90.85% versus the corresponding best MLP performance of only 81.20%. The DCNN has led to the best (minimum) MAR of 3.81% (having at the same time OA greater than 90%), while the MLP has obtained a minimum MAR of only 32.81%. On the other side, the best overall classification scores of over 90% obtained by our credit scoring prediction model based on DCNN are clearly higher than the average classification score of 85.33% reported in literature for German credit data [1].

For the Australian credit dataset, the proposed DCNN leads to the best OA of 99.74%, in comparison with the corresponding best MLP performance of 90.75%. The DCNN has led to the best (minimum) MAR of 0% versus the best MAR obtained by MLP of 8.64%. At the same time, the best overall classification score of 99.74 % obtained by the proposed credit scoring prediction model based on DCNN is significantly higher than the average classification score of 89.59% reported in literature for Australian credit data [1].

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AN ENSEMBLE OF DEEP CONVOLUTIONAL NEURAL NETWORKS FOR DRUNKENNESS DETECTION USING THERMAL INFRARED FACIAL IMAGERY

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***Abstract*— This paper proposes an original method for subject independent drunkenness detection using an ensemble of Deep Convolutional Neural Networks (DCNNs) for processing of thermal infrared facial imagery characterizing the subjects to be tested. The proposed neural system consists of an ensemble of two DCNNs modules for thermal infrared facial image processing; the first module is composed by 12 layers and the second one has 10 layers. The two DCNNs have been trained separately, using different architectures and different sets of parameters. The final decision is influenced by the confidence degrees of two CNN component modules. The proposed method is evaluated using the dataset of 400 thermal infrared facial images belonging to 10 subjects. For each subject the dataset contains 20 thermal images corresponding to sober condition and other 20 images for inebriation condition obtained 30 minutes after the subject has drunk 100 ml amount of whisky. The experiments of the proposed DCNN couple for subject independent drunkenness detection lead to the overall correct detection score of 95.75%. This confirms the effectiveness of the proposed approach.**

Keywords*— *Drunkenness detection, deep learning, deep convolutional neural networks (DCNN), thermal infrared imagery

I. INTRODUCTION

Drunkenness is a challenging physiological condition to be investigated with applications to test driver (sober/drunk) condition [1]. Drunk driving is often a symptom not only of alcohol problems but also of others as drug, unemployment, legal status and psychosocial problems [1]. The reported proportion of drivers with alcohol problems varies between no less than 4% and 87% in different investigations in Sweden, depending on the method of drunkenness definition.

Reports as [2] covering 99% of the world population are showing drunk driving (along with speeding and failing to use the regulated safety equipment as belts and helmets), as having a significant impact on traffic related deaths. Total traffic related deaths in 2013 were 1.24 million and the number is increasing with a fast pace. In US, drunk drivers were involved in 28% of the traffic accidents with fatalities [19].

Most of the publications regarding drunkenness diagnosis refer only to automotive anti-drunk driving systems, which use electrical signals from the heart or brain [3]. On the other side, the use of thermal infrared (IR) images can improve the performance of face recognition in biometric applications under uncontrolled illumination conditions [4], [5]. Published research [5], [7] is corelating the increase for of the blood flow of a person face with the consumption of alcohol. This effect was underlined [6], [7] with the use of thermal cameras. The images of the thermal cameras can be analyzed with more and more sophisticated image processing and patterns recognition techniques as shown in [8], [9]. A recent successful approach of drunkenness detection using neural networks for thermal infrared imagery has been proposed by Neagoe and Carata [10], [11]. It consists of a processing cascade composed by the Pulse-Coupled Neural Network (PCNN) for image segmentation followed by feature selection and Support Vector Machine (SVM) classifier.

This paper proposes an original method for drunkenness detection using an Ensemble of two Deep Convolutional Neural Networks (DCNNs) for processing of the thermal infrared facial imagery of the subjects to be tested. We have chosen the variant of subject independent drunkenness recognition implying the procedure of building training datasets for each of the J subjects, using the images of the other (J-1) ones different of the considered subject. The main objective of our research is to obtain a correct detection rate of more than 90% for both of the drunk and sober states. The model is evaluated using the dataset of 400 thermal infrared images corresponding to J=10 subjects mentioned in [10], [11].

II. PROPOSED MODEL BASED ON THE COUPLE OF CONCURRENT DCNNS

A. *Deep Convolutional Neural Networks*

Some attempts have recently been made to use deep learning (DL) techniques and especially convolutional neural networks (CNNs) for pattern classification in medical imagery, after their impressive performance in large scale color image classification, as well as searching and recognizing objects in images [12], [13], [14], [15], [16].

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Convolutional Neural Networks are used in various of application due to their capacity to extract features and use these features to recognize and classify objects. Variations of CNNs include layers with different primitive functions: convolution, dropout, activation (as rectifier), fully-connected, soft-max, classification and others.

Convolutional layers have their neurons connected to all neurons from certain areas of the previous layer. These neurons are organized as feature maps that execute convolutions of the previous layer. All the weights for a neuron from convolutional layer are creating together a filter.

The dropout layers are used to pass the information from some of the neurons from previous layer, while ignoring the information sent by others, reducing this way the over-fitting.

The rectifier layer contains an activation mechanism. When activated by a value higher than a threshold, the input of the neuron can be sent to next layer.

The fully connected layer has its neurons connected to all activations from the previous layer. Their output is a result of computations between the previous layer and fully connected weights, the principle being the same as in case of the multi-layer perceptron (MLP).

The Soft-max layer is a layer that is increasing the probability of the maximum value of the previous layer compared to other values.

The classification layer is an output layer that provides probabilities for each of the existing classes.

B. Proposed model

There are a few examples of neural processing systems using an ensemble of modular neural networks [8], [17], [18]. Inspired by the above-mentioned works, this paper proposes to process the input facial thermal infrared image for inebriation detection using a neural system composed by an ensemble of two DCNNs (see Fig. 1).

The two DCNN modules of the ensemble have 12 layers and respectively, 10 layers. The difference is made by the third convolutional layer (with an additional dropoutLayer) used in only one of the networks.

TABLE I. ARCHITECTURE OF THE DCNN MODULES

Layer number	DCNN-1	DCNN-2
1	imageInputLayer	imageInputLayer
2	convolution2dLayer	convolution2dLayer
3	dropoutLayer	dropoutLayer
4	convolution2dLayer	convolution2dLayer
5	dropoutLayer	dropoutLayer
6	convolution2dLayer	fullyConnectedLayer
7	dropoutLayer	reluLayer
8	fullyConnectedLayer	fullyConnectedLayer
9	reluLayer	softmaxLayer
10	fullyConnectedLayer	classificationLayer
11	softmaxLayer	
12	classificationLayer	

The two DCNNs have been trained separately, by using only some common parameters, the rest of parameters being different, as shown in Table I. Consequently, there are two independent DCNNs with independent decisions . The final decision mechanism works like this:

(a) When both DCNNs lead to the same decision (drunk or sober), we consider that common result as final

(b) When the two DCNNs lead to different decisions, higher confidence result is selected as a final decision.

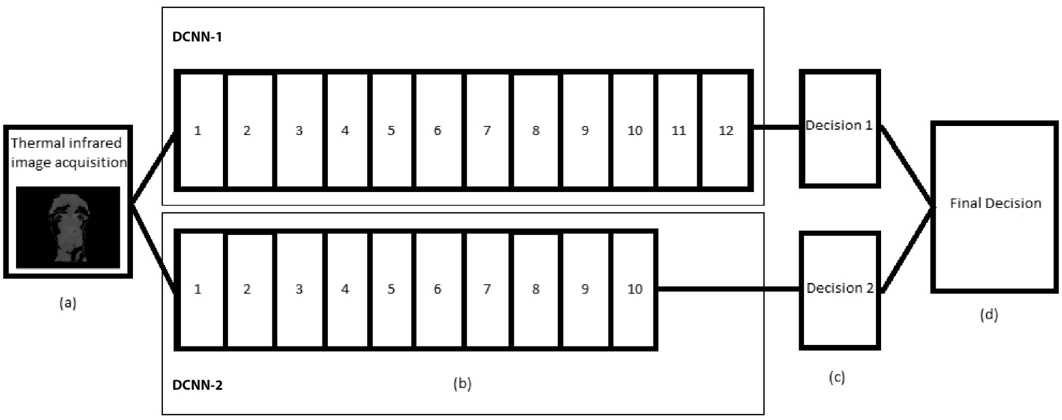

Fig. 1. An ensemble of two DCNNs architecture for subject independent drunkenness detection: (a) loading of the thermal infrared image; (b) the two DCNNs with 12 and 10 layers; (c) detection results for each of the two DCNNs; (d) Final decision result given by fusion of the component decisions.

III. Experiments

A. Thermal image dataset

We have used the dataset of thermal infrared images built by Neagoe and Carata [10], [11]. The dataset contains 400 images at a resolution of 160 x 120 pixels. The images taken with a FLIR ThermaCAM B2 camera contain faces of J=10 subjects (Fig. 2) in sober or drunk state. For the sober images, 20 photos of each subject were taken before any alcohol quantity was tasted. For the drunk images, 20 photos of each subject were taken 30 minutes after each person drank 100 ml of whisky. This quantity was considered sufficient to produce a dilatation of face sanguine vessels with the effect of face temperature increase. Although there was not in the objective of our work to measure the alcoholemy and correlate it with blood vessel dilatation, we have estimated a 0.5mg/l average alcoholemy for the subjects in drunk state.

Fig. 2. Subjects whose facial images have generated the database

An example of thermal facial images corresponding to sober/drunk conditions of the same subject is given in Fig. 3.

Fig. 3. Thermal facial images characterizing the same subject in the two conditions: (a) sober; (b) drunk.

B. Training and parameter setup

Additional 720 virtual images have been generated (72 artificial pictures/class) by rotating the original images to the left and right. The reason of this operation was to obtain training data augmentation, to reduce overfitting.

We have chosen a procedure of subject independent drunkenness recognition implying to build training, validation and test datasets for each of the J=10 subjects. Namely, for each of the subject of index "i" (i=1…10), we have built the training dataset LSi, containing 324 original images of the other 9 subjects (36 images for each subject) as well as 648 virtually generated images of the same 9 subjects, half in drunk state, half in sober state. For the same subject "i", we have also prepared a validation set VSi, with 36 original images of subject "i", and a test set TSi, containing 40 original pictures of the same subject.

The application has been implemented in MATLAB. We have trained 10 neural systems, one for each subject, each neural module being composed by a couple of concurrent CNNs. In fact, the same CNN module architecture has been used ten times, but with different sets of training, validation and test.

The initial network weights have been randomly generated. For selecting the most appropriate parameters for training, multiple combinations of parameter values have been tried in the ranges shown in Table II.

TABLE II. Ranges for some relevant training DCNN parameters and optimized values of training parameters that lead to the best classification results

Training parameter	**Parameter ranges tried for finding the optimum parameters**	**Optimum set of CNN parameters for subject independent drunkenness detection**	
		DCNN 1	***DCNN 2***
Number of network layers	[8 – 15]	12 layers	10 layers
Filter size	[3x3-20x20]	3 x 3	3 x 3
Number of convolutional filters	[8-128]	32	24
InitialLearnRate	[0.00001..0.01]	0.001	0.001
MaxEpochs	[10-500]	30	20
MiniBatchSize	[6-256]	80	32
Training Algorithm	SGDM, ADAM	SGDM	SGDM
Momentum for SGDM Algorithm	[0.1-0.9]	0.1	0.1
Training Accuracy Threshold	[90%-99%]	95%	95%

IV. RESULTS

The results of subject independent drunkenness detection are given in Table III, both as individual performance for each subject and as an overall performance. One can deduce a minimum correct detection rate of 90% for subject number 7, a maximum rate of 97.5% for subjects numbers 2, 3, 6, 8 and 10, as well as an overall detection rate of 95.75%.

TABLE III. SUBJECT INDEPENDENT DRUNKENNESS DETECTION RATE

Index of the test subject for drunkenness detection with the neural couple of CNNs trained on the other 9 subjects	**DCNN 1**	**DCNN 2**	**Ensemble of two DCNNs**
1	90.00%	95.00%	95.00%
2	97.50%	95.00%	97.50%
3	95.00%	92.50%	97.50%
4	95.00%	95.00%	95.00%
5	92.50%	90.00%	95.00%
6	97.50%	95.00%	97.50%
7	90.00%	87.50%	90.00%
8	92.50%	90.00%	97.50%
9	92.50%	92.50%	95.00%
10	90.00%	95.00%	97.50%
Average Correct Detection Rate	93.25%	92.75%	95.75%
Standard Deviation	3.89%	3.69%	3.18%

V. CONCLUSIONS

The presented method of subject independent drunkenness diagnosis represents an exciting combination of modern technology techniques: thermal infrared image processing and deep learning based on CNNs. One main novelty of the method is that the proposed neural system is composed by an ensemble of DCNNs trained to process the input thermal facial images. The advantages of the system based on the ensemble of two DCNNs over a single DCNN module are the following:

(a) better drunkenness detection performance: 2.5% more compared with the case of using a single DCNN

(b) more training environment flexibility given by the fact the DCNNs from the ensemble can be run simultaneously on different hardware for the entire training stage.

The overall correct inebriation detection performance of 95.75% confirms the effectiveness of the proposed approach by comparison with the state of the art techniques.

Moreover, the presented DCNN system has the obvious advantage that it performs both feature selection and classification, thus avoiding the necessity to use old cumbersome and time-consuming techniques for feature selection.

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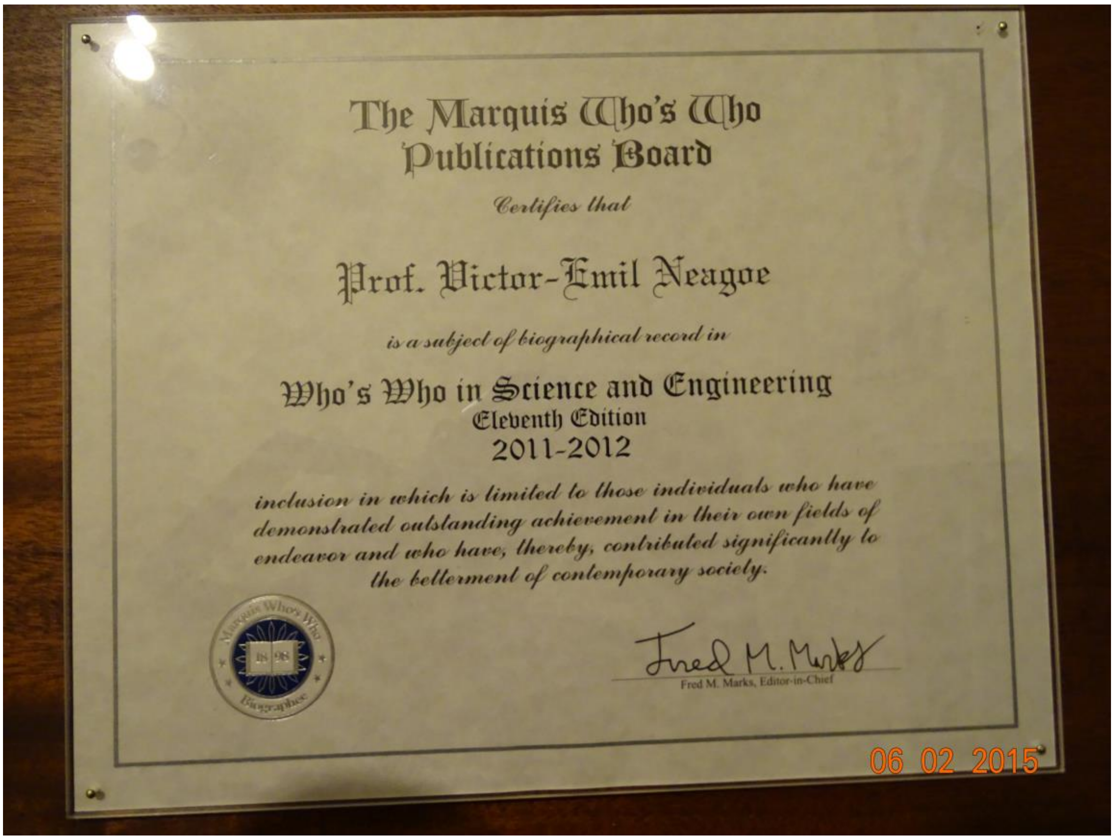

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