FUNDING APPLICATION FOR

EXPLORATORY RESEARCH PROJECTS - PN-II-ID-PCE-2011-3

Section 3

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B. Project leader

B1. Scientific visibility and prestige (maximum 2 pages)

B.1.1. *Main research results.*

After working mainly in parallel algorithms for numerical computation, I started signal processing research in 1998. The main theme was the use of convex optimization, particularly of semidefinite programming, to applications typical to signal processing. Most of the results are gathered in the monograph *Positive trigonometric polynomials and signal processing applications*, published at Springer in 2007. The most significant results are:

- The parameterization of *positive trigonometric polynomials* through positive definite matrices (2001, art.26 in publication list), allowing the use of semidefinite programming for solving optimization problems with such polynomials, like in the design of two-channel orthogonal filter banks or MA spectrum estimation. The parameterization allows an exact solution to the optimization problems, while earlier methods based on discretization could give only an approximation.

- The *sum-of-squares* approach for *multidimensional* trigonometric polynomials that are positive on certain sets and its application to 2D FIR filter design (2006, art.13, 10).

- A *Bounded Real Lemma* for FIR systems in linear matrix inequality (LMI) form, including the multidimensional case (2005, art.16). This is a unique type of result.

- An LMI description of *convex stability domains* for transfer functions (2004, art.17,18) that can be used in the optimization of IIR filters.

- An LMI characterization of *positive real rational transfer functions* with fixed poles (2002, art 24), with applications to model order reduction.

- The use of convex optimization techniques for the optimization of the *dual tree complex wavelet* and related wavelet-generating filter structures (2008, art.3, 6, 8).

- The use of convex optimization techniques for the design of *oversampled filter banks* (2006, art. 5, 15). This work has led also to three patent applications together with Nokia Research Center, Tampere, Finland.

- The design of the software library POS3POLY (2010) for optimization with positive polynomials, see www.schur.pub.ro/pos3poly.

Due to the use of convex optimization in finding sparse solutions to linear systems, I followed closely the emergence of sparse representation methods in signal processing. However, the main contribution (in the form of two conference papers, a journal article being in preparation) was in a *greedy recursive least squares (RLS) algorithm* for FIR filters, which is the first greedy algorithm of this kind and competes very well with the counterparts resulting from a convex relaxation approach.

B.1.2. *The visibility of the scientific contributions.*

- Associate editor (since 2008) and area editor (since 2010) at IEEE Transactions on Signal Processing, the leading journal in the field.
- Technical program committee member at several editions of the European Signal Processing Conference (EUSIPCO), including 2011, and also at other signal processing conferences.
- Collaboration with top scientists like Ivan Selesnick (New York) in wavelet design and Lieven Vandenberghe (UCLA) in convex optimization.
- Invited talks at Tampere University of Technology and Drexel University.

B2. Curriculum vitae (*max. 4 pages****)***

Date/place of birth: May 7, 1962, Bucharest, Romania

a) Education

- 1993: Ph.D. degree at the ”Politehnica” University of Bucharest (PUB). Thesis title: “Parallel computation systems and algorithms”.
- 1987: M.Sc. degree at the Department of Automatic Control and Computers, PUB.

b) Professional experience

- 1.10.2003 – present : professor at the Department of Automatic Control and Computers, ”Politehnica” University of Bucharest and researcher at Tampere International Center for Signal Processing (Tampere University of Technology-TUT).
- 1.10.1990 – 1.10.2003: various teaching positions at the Department of Automatic Control and Computers, PUB.
- 1992 – 1996: three stages (15 months) as researcher, Universite Polytechnique de Grenoble, France
- 1.10.1987 - 1.10.1990: software engineer at FEPER Bucharest (Peripheral Equipments Factory).

At PUB I teach Numerical Methods, Scientific Computation and Advanced Signal Processing and I taught several other courses like Signal Processing, Parallel Algorithms, Convex Optimization. I also gave in 2010 a course on Scientific Writing. I am a PhD adviser since 2007 and currently have 3 PhD students.

At TUT I do mostly research, oriented on convex optimization and its applications in signal processing. A part of this research has been done in cooperation with Nokia Research Center (3 pending patent applications). Currently, I am a FiDiPro fellow for the period 2010-2013. FiDiPro (Finnish Distinguished Professor, see www.fidipro.fi) programme has the purpose of supporting “top international experts” who work together with Finnish teams of researchers for about half of their time. The team in which I work has two other professors and two PhD students. One of the research themes is related to sparse representations and their use for audio coding, like for example in lossless audio compression.

c) Publications

ISI journals articles (29)

1. B.Dumitrescu, B.C.Sicleru, R.Stefan - Positive hybrid real-trigonometric polynomials and applications to adjustable filter design and absolute stability analysis, Circuits, Systems and Signal Processing, vol.29, no.5, pp.881-899, Oct. 2010.
2. B.Dumitrescu - A Moulding Technique for the Design of 2-D Nearly Orthogonal Filter Banks, IEEE Signal Processing Letters, vol.17, no.3, pp.261-264, March 2010.
3. B.Dumitrescu - Optimization of the Higher Density Discrete Wavelet Transform and of its Dual Tree, IEEE Trans. Signal Processing, vol.58, no.2, pp.583-590, Feb. 2010.
4. B.Dumitrescu, B.C.Sicleru, R.Stefan - Computing the Controllability Radius: a Semidefinite Programming Approach, IET Control Theory & Applications, vol.3, no.6, pp.654-660, June 2009.
5. B.Dumitrescu, R.Bregovic, T.Saramäki - Design of Low-Delay Nonuniform Oversampled Filterbanks, Signal Processing, vol.88, no.10, pp.2518-2525, Oct. 2008.
6. B.Dumitrescu - SDP Approximation of a Fractional Delay and the Design of Dual-Tree Complex Wavelet Transform, IEEE Trans. Signal Processing, vol.56, no.9, pp.4255-4262, Sept. 2008.
7. B.Dumitrescu - LMI Stability Tests for the Fornasini-Marchesini Model, IEEE Trans. Signal Processing, vol.56, no.8, pp.4091-4095, Aug. 2008.
8. B.Dumitrescu, I.Bayram, I.Selesnick - Optimization of Symmetric Self-Hilbertian Filters for the Dual-Tree Complex Wavelet Transform, IEEE Signal Processing Letters, vol.15, pp.146-149, 2008.
9. B.Dumitrescu - Comments on "Design of an Optimal Two-Channel Orthogonal Filterbank Using Semidefinite Programming", IEEE Signal Processing Letters, vol.15, p.111, 2008.
10. T.Roh, B.Dumitrescu, L.Vandenberghe - Multidimensional FIR Filter Design via Trigonometric Sum-of-Squares Optimization, IEEE J. Sel. Topics Sign. Proc., vol.1, no.4, pp.641-650, Dec. 2007.
11. B.Dumitrescu - Positivstellensatz for Trigonometric Polynomials and Multidimensional Stability Tests, IEEE Trans. Circuits & Systems II, vol.54, no.4, pp.353-356, April 2007.
12. B.Dumitrescu - Trigonometric Polynomials Positive on Frequency Domains and Applications to 2-D FIR Filter Design, IEEE Trans. Signal Processing, vol.54, no.11, pp.4282-4292, Nov. 2006.
13. B.Dumitrescu, B.C.Chang - Robust Schur Stability with Polynomial Parameters, IEEE Trans. Circuits & Systems II, vol.53, no.7, pp.935-937, July 2006.
14. B.Dumitrescu - Stability Test of Multidimensional Discrete-Time Systems via Sum-of-Squares Decomposition, IEEE Trans. Circuits & Systems I, vol.53, no.4, pp.928-936, April 2006.
15. B.Dumitrescu, R.Bregovic, T.Saramäki - Simplified Design of Low-Delay Oversampled NPR GDFT Filterbanks, EURASIP Journal on Applied Signal Processing, vol. 2006, Article ID 42961, 11 pages, 2006.

16. B.Dumitrescu - Bounded Real Lemma for FIR MIMO Systems, IEEE Signal Processing Letters, vol.12, no.7, pp.496-499, July 2005.
17. B.Dumitrescu - Optimization of 2-D IIR Filters with Nonseparable and Separable Denominator, IEEE Trans. Signal Processing, vol.53, no.5, pp.1768-1777, May 2005.
18. B.Dumitrescu, R.Niemistö - Multistage IIR Filter Design Using Convex Stability Domains Defined by Positive Realness, IEEE Trans. Signal Processing, vol.52, no.4, pp.962-974, April 2004.
19. R.Niemistö, B.Dumitrescu - Simplified Procedures for Quasi-Equiripple IIR Filter Design, IEEE Signal Processing Letters, vol.11, no.3, pp.308-311, March 2004.
20. C.Popeea, B.Dumitrescu, B.Jora - Efficient State-Space Approach for FIR Filter Bank Completion, Signal Processing, vol.83, no.9, pp.1973-1983, Sept. 2003.
21. B.Dumitrescu, C.Popeea - Accurate Computation of Compaction Filters with High Regularity, IEEE Signal Processing Letters, vol.9, no.9, pp.278-281, Sept. 2002.
22. R.Niemistö, B.Dumitrescu, I.Tabus - SDP Design Procedure for Near-Optimum IIR Compaction Filters, Signal Processing, vol.82, no.6, pp.911-924, June 2002.
23. A.Vasilache, B.Dumitrescu, I.Tabus - Multiple Scale Leader Lattice VQ with Application to LSF Quantization, Signal Processing, vol.82, no.4, pp.563-586, April 2002.
24. B.Dumitrescu - Parameterization of Positive Real Transfer Functions with Fixed Poles, IEEE Trans. Circ. Syst. I, vol.49, no.4, pp.523-526, April 2002.
25. B.Dumitrescu, I.Tabus, P.Stoica - On the Parameterization of Positive Real Sequences and MA Parameter Estimation, IEEE Trans. Signal Processing, vol.49, no.11, pp.2630-2639, Nov. 2001.
26. B.Dumitrescu, I.Tabus - Predictive LSF Computation, Signal Processing, vol.81, no.10, pp.2019-2031, Oct. 2001.
27. C.Popeea, B.Dumitrescu - Optimal Compaction Gain By Eigenvalue Minimization, Signal Processing, vol. 81, no.5, pp.1113-1116, May 2001.
28. B.Dumitrescu - Improving and Estimating the Accuracy of Strassen's Algorithm, Numerische Mathematik, vol.79, no.4, pp. 485-499, April 1998.
29. B.Dumitrescu, M.Doreille, J.L.Roch, D.Trystram - Two-Dimensional Block Partitionings for the Parallel Cholesky Factorization, Numerical Algorithms, vol.16, no.1, pp. 17-38, 1997.

Other journals articles (9) : published in Romanian (Control Engineering and Applied Informatics, Revue Roum. Sci. Techn. Electrotechn. Energ., Studies in Informatics and Control) and other (Parallel Algorithms and Applications) journals.

Books (1 monograph, 1 textbook, listed below, and several others, mostly in electronic form**)**

1. B.Dumitrescu - Positive Trigonometric Polynomials and Signal Processing Applications, Springer, 2007.
2. B.Dumitrescu, C.Popeea, B.Jora - Numerical Methods for Matrix Computation. Fundamental Algorithms, ALL, Bucharest, 1998 (in Romanian).

Conference papers (63)

15 conference papers are indexed in ISI Proceedings, among which 8 were presented at ICASSP, the leading conference in signal processing (acceptance rate about 50%). From the other papers, 9 were presented at EUSIPCO, the leading European signal processing conference. Of relevance to this project are the papers

B.Dumitrescu, I.Tabus - Greedy RLS for Sparse Filters, *EUSIPCO*, Aalborg, Denmark, Aug. 2010.

A.Onose, B.Dumitrescu, I.Tabus - Sliding Window Greedy RLS for Sparse Filters, *ICASSP*, Prague, Czech Republic, May 2011.

A **complete publication list** can be found at www.schur.pub.ro/BD_PublicationList.html.

Recent grants

IDEI (2007-2010) “Positivity in the analysis and synthesis of multidimensional systems”, 567421 lei. The direct results of this project were 4 ISI journal articles, several conference papers and the software library POS3POLY, see www.schur.pub.ro/pos3poly.

d) Hirsch index (given by researcher ID): 6

Total number of citations (given by researcher ID): 148

Additionally, the monograph “Positive Trigonometric Polynomials and Signal Processing Applications” has 25 citations on isiknowledge.com.

e) Researcher ID profile: B-5839-2011.

B3. Scientific contributions from the period 2001-2011

Articles

1. B.Dumitrescu, I.Tabus, P.Stoica - On the Parameterization of Positive Real Sequences and MA Parameter Estimation, IEEE Trans. Signal Processing, vol.49, no.11, pp.2630-2639, Nov. 2001.
No. of citations: 27
Summary: This is one of the first articles that present the parameterization of positive trigonometric polynomials via positive semidefinte matrices, opening the possibility of using semidefinite programming as a tool for many problems in signal processing and control.

2. B.Dumitrescu - Trigonometric Polynomials Positive on Frequency Domains and Applications to 2-D FIR Filter Design, IEEE Trans. Signal Processing, vol.54, no.11, pp.4282-4292, Nov. 2006.
No. of citations: 11
Summary: An extension of the previous parameterization to partial positivity and the 2D case. First method of this type for designing 2D FIR filters ; contrary to all previous methods, optimization is not performed on a discretization grid, but fully accounts the passband and stopband regions.

3. B.Dumitrescu - Parameterization of Positive Real Transfer Functions with Fixed Poles, IEEE Trans. Circ. Syst. I, vol.49, no.4, pp.523-526, April 2002.
No. of citations: 13
Summary: The first explicit parameterization of this type.

4. B.Dumitrescu, R.Niemistö - Multistage IIR Filter Design Using Convex Stability Domains Defined by Positive Realness, IEEE Trans. Signal Processing, vol.52, no.4, pp.962-974, April 2004.
No. of citations: 13
Summary: A method for designing IIR filters using an original contraint for enforcing stability.

5. B.Dumitrescu - Optimization of 2-D IIR Filters with Nonseparable and Separable Denominator, IEEE Trans. Signal Processing, vol.53, no.5, pp.1768-1777, May 2005.
No. of citations: 6
Summary: An extension of the previous to the 2D case.

6. B.Dumitrescu - Bounded Real Lemma for FIR MIMO Systems, IEEE Signal Processing Letters, vol.12, no.7, pp.496-499, July 2005.
No. of citations: 4

Summary: First linear matrix form of a Bounded Real Lemma for FIR systems, later generalized to the multidimensional case.

7. B.Dumitrescu, C.Popeea - Accurate Computation of Compaction Filters with High Regularity, IEEE Signal Processing Letters, vol.9, no.9, pp.278-281, Sept. 2002.
No. of citations: 3
Summary: An efficient semidefinite programming method for optimizing two-channel FIR filter banks, and hence wavelets, with arbitrary number of regularity conditions.

8. B.Dumitrescu, I.Bayram, I.Selesnick - Optimization of Symmetric Self-Hilbertian Filters for the Dual-Tree Complex Wavelet Transform, IEEE Signal Processing Letters, vol.15, pp.146-149, 2008.
No. of citations: 3
Summary: An original description of the space of filters generating dual-tree complex wavelets and its use for optimization in a few practical cases.

9. B.Dumitrescu - SDP Approximation of a Fractional Delay and the Design of Dual-Tree Complex Wavelet Transform, IEEE Trans. Signal Processing, vol.56, no.9, pp.4255-4262, Sept. 2008.
No. of citations: 4
Summary: A new linear matrix inequality for approximating a rational fractional delay and its use for the optimization of dual-tree complex wavelets.

Monograph
10. B.Dumitrescu - Positive Trigonometric Polynomials and Signal Processing Applications, Springer, 2007.
Number of citations in ISI: 17
No. of libraries in worldcat.org: 238 apparently, but some may have only electronic access, since the book has been made electronically available in 2009 by Springer.
University libraries: Library of Congress, MIT Libraries, Columbia University, Rutgers University, University at Albany, University of Washington Libraries, University of Massachussets Amherst, Stanford University, Purdue University, University of Iowa.

Note : the number of citations has been taken from isiknowledge.com, without considering self citations.

C. Project description (max. 10 pages)

Project title: Sparse representations in signal processing

C1. *Scientific context and motivation*

In a general view, a model is sparse if many of its coefficients are zero. For example, the solution of the linear system $Ax=b$, with A an mxn matrix, is sparse if the number of nonzero elements of x, denoted $||x||_0$ (and improperly named 0-norm of the vector), is much smaller than n. Typically, the system is overdetermined, i.e. $m<n$, which means that it has an infinite number of solutions; however, the sparsest solution may be unique. The matrix A is often called dictionary (whose words are the columns of A); the solution x gives the representation of the vector b in the dictionary. Another example is that of an FIR filtering model; if $x(t)$, $y(t)$ are the input and output of a discrete-time process, one can model the process by $y(t)=\sum_{i=0}^{n} h_i x(t-i)+e(t)$, where $e(t)$ is the noise. The FIR filter $H(z)$ has order n and is sparse if many of the coefficients h_i are zero. The least-squares filter design problem, like many others, can be reduced to finding a sparse approximate solution to a linear system whose matrix depends on the input and output samples. The positions of the nonzero elements of the solution is called support (for filters, this is the natural definition).

Sparse models have gained attention in the latest decade due to their intrinsic parsimonious nature. They are able to express the properties of a system or phenomenon with relatively small complexity and so they may capture the true features better than a full model. We give below a few relevant directions of research, starting from theory and going to signal processing applications.

Basic theory. The foundations of the field are described in the review paper [BDE09] and the (only) book [Elad10]. The main results regard the conditions under which a sparse solution of the overdetermined system $Ax=b$ is indeed the sparsest. The conditions are expressed in terms of properties of the columns of A, like the smallest angle between two columns (mutual coherence) or the smallest number of linearly dependent columns (spark). The analysis was also extended to the noisy case, where $||x||_0$ is maximized under the constraint $||b\text{-}Ax||_2<\varepsilon$, where ε is an accepted error.

General algorithms. There are two main classes of practical algorithms for finding sparse solutions to linear systems; note that finding the sparsest solution is NP-hard in general and so the algorithms are not guaranteed to give the optimal solution, although this happens in quite many situations. *Greedy* algorithms select the nonzero positions one by one, each time adding the most promising (according to some heuristic) position to the already selected ones. The standard greedy algorithms are matching pursuit [MaZh93], orthogonal matching pursuit, orthogonal least squares

[CBL89,RL02]; there are many recent variations, in which several positions are added simultaneously and then some are removed, like subspace pursuit [DaMi09, VKT11] or CoSaMP [NeTr09]. The second class consists of convex relaxations techniques, in which the non-convex sparsity measure $||x||_0$ is replaced by its convex approximation $||x||_1$; the generic name of this approach is *basis pursuit* [CDS98]. The resulting convex optimization problem can be solved with linear programming or second-order cone programming algorithms; alternatively, dedicated algorithms have been developed. Efforts in proving the properties of the algorithms are still being made [DaWa10]. Most of the previous work minimizes or bound the 2-norm of the residual, hence finds a least-squares (LS) solution. In [GCM10], the 1-norm of the residual is minimized, in the hope of obtaining sparse residuals that are better suited to speech coding. A promising research direction is the *total least squares* (TLS) approach, until now tackled only in [ZLG11], with a coordinate descent algorithm; the problem is harder than the LS approach, as perturbations can affect also the matrix A, and cannot be easily relaxed to convex form, hence the choice from [ZLG11]. This makes greedy algorithms an interesting choice, open to investigation. A connection can be made with the greedy algorithm for computing the restricted isometry constants [DPF10], where a singular value of a group of columns of A has to be minimized, somewhat similar to the TLS case.

Algorithms for applications. There are several signal processing applications where sparse representations have been shown at least promising, if not better than other approaches. We ignore completely image processing applications (see [BDE09] for an example) and list only directions of research that are close to our interests:

- Although filter design is an old subject in signal processing, the design of *sparse filters*, with the aim of reducing their implementation complexity, has many challenges, due to its combinatorial nature. It has been attempted with greedy techniques in [BWO10], for the 1D case, and with convex relaxations in [LuHi11], for the 2D case. There are significant possibilities of improving the results, taking advantage of the wealth of available general algorithms and of combinations between them.

- *Recursive least squares* (RLS) for sparse channel identification has potential applications in e.g. wireless communications in urban areas, where different deflection paths introduce different delays. The development of sparse RLS algorithms is only at its beginning; convex relaxation techniques have been used in [ABG10,BKT10], while a greedy algorithm was proposed in [DuTa10]. Sparse adaptive filtering and the RLS algorithm in particular appear to have significant room for improvement.

- *Speech coding* techniques in [GCM10] (see also other papers by Giacobello et al) use sparse predictors, computed with linear programming. This can represent an improvement of ACELP coders, but also may pose problems for real-time computation.

Dictionary optimization for sparse modeling is a somewhat distinct topic, as it may belong more to machine learning than to signal processing. Given a sufficiently large number of sample vectors b, the purpose is to create a matrix A such that the representations $Ax=b$ are possible with sparse vectors x. Hence, the dictionary is tailored to the process generating the data. This is opposed to the case where the dictionary is made of some heuristically selected vectors (e.g. by joining orthogonal bases corresponding to some standard transforms). Basic methods for dictionary optimization are the Method of Optimal Directions (MOD) [EAH00] and K-SVD [AEB06]. Alternative methods may seek a recursive optimization, see e.g. [SkEn10], where the sample data vectors are used only once, in the order in which they become available. Optimized dictionaries can be used for empirical classification: first, dictionaries A_1, A_2, …, are trained for different categories of data (e.g. audio recordings of pieces belonging to a music genre); then, when new data (music pieces) are available, they are represented with each of the dictionaries A_i; the category (genre) is given by the dictionary allowing the best representation. In the context of sparse representations, "best" means either the sparsest for similar residuals or that giving the smallest residual for the same sparsity. A discussion of music genre classifications can be found in [PKA10] and previous papers of the same authors (not necessarily related to sparse dictionaries). Of course, if the data have very large size (at least millions of samples for a music piece), it is important to select relevant features before attempting the classification and this is a problem in itself. A technique that can improve the classification is discriminative learning [MBP08], in which the dictionaries are not only optimized to represent well the training vectors from their category, but also to have worse representations for vectors from other categories. Due to the large quantity of data and of the complex optimization tasks involved by dictionary training, the topic of dictionary optimization is still subject to intense research.

Distributed algorithms. In some applications, for example related to sensor networks, it is desirable to process data locally as much as possible, due to the high cost of communication; this is necessary also in other situations, when communication is not desired for protecting the local data, while the result of the processing can be transmitted without affecting privacy. These are reasons for developing distributed algorithms instead of centralizing the data and processing them on a single computing unit; such algorithms assume that the computation is made on many processors and communication has low volume and is made only with few "neighbors". Sparse representations pose extra difficulties, because not only the relevant values should be computed, but also the support of the solution must be agreed upon on the ensemble of processors. Despite a revival of signal processing distributed algorithms in the recent years (see e.g. [MSG09] for a distributed RLS), the only algorithm that deals with sparse representations seems to be [MBG10], where sparse linear regression is tackled with a distributed convex relaxation approach. Although greedy algorithms seem less amenable to a distributed treatment, they may be significantly faster than convex relaxation. Extensions to more difficult filtering problems are certainly possible.

Expertise and motivation. Although I have spent most of the last decade working on a different topic (optimization with positive polynomials), I have followed the developing field of sparse representations since 2005, due to its relation with convex optimization. Since the beginning of 2010, I have started actively working in this field, in cooperation with a small group at Tampere University of Technology, Finland (TUT). The most significant results are in a greedy RLS algorithm for sparse filters [DuTa10,ODT11] that appear to give better results than [ABG10], [BKT10] (a journal article is in preparation, the applications being in lossless audio compression). The motivation of this project is not only the large number of open issues and applications related to or using directly sparse representations, but also the desire to create at Politehnica University a group with significant competence on this modern topic. Our background in signal processing, optimization and numerical computation (including parallel algorithms) offers a good starting point.

C2. ***Objectives***

The main research topics and the objectives to be reached are the following:

O1. Sparse filters design. The purpose is to obtain 1D and 2D sparse FIR filters that are better than those currently available [BWO10,LuHi11]. The techniques that prove valuable will be employed for other problems, like e.g. the design of sparse filter banks. Although it is unlikely that significant innovation is possible, this topic is fit for starting, as it is strongly related to previous work of the research team.

O2. Sparse total least squares. The TLS is an alternative to least-squares, taking into account a more general class of perturbations. However, the amount of research on the corresponding sparse problems is completely unbalanced: the only paper for sparse TLS is [ZLG11], while there are maybe hundreds of papers on sparse LS. We plan to investigate greedy algorithms for sparse TLS and also analyze significant properties of the sparse TLS problem, like for example under what conditions the TLS and LS (or regularized LS) solutions have the same support.

O3. Distributed sparse filtering. Distributed applications are more and more required in a signal processing world where the number of processors is continually growing, but for economic reasons they are as simple as the application allows. Our aim is to study distributed filtering algorithms, with emphasis on sparse problems. The target problem is sparse RLS, for which we already have an innovative centralized greedy approach [DuTa10]. However, the distributed problem is far more complicated and involves different techniques. We aim to design distributed algorithms for sparse filtering that have similar performance (steady-state error, convergence speed) to the centralized best algorithms [ABG10,BKT10,DuTa10].

O4. Classification with sparse predictors. Automatic classification is an essential task in the wealth of information produced today. We plan to analyze only 1D information (audio, not images or video) using sparse linear predictors as the main tool. Such predictors with only few nonzero elements may be able to capture essential information on the fine structure of sound and may have the potential to discern between sounds produced by different types of sources. Given training audio sequences, our aim is to optimize dictionaries for sparse representation of samples from each category, with the final purpose of serving as classifiers. An example of classification problem is that of music genre (like e.g. classical, jazz, rock, etc.); see the MIREX (Music Information Retrieval Evaluation eXchange) site (http://www.music-ir.org/mirex) for other types of problems. It is likely that sparse predictors alone are not able to achieve the best results, due to their local nature, hence they will have to be combined with other features, expressing global characteristics. We hope to obtain top quality results that will be validated through publications and participation to the MIREX competitions.

Publication objective. We plan to publish at least an ISI journal article for each of the objectives **O1-O3** and several conference papers at top signal processing conferences (ICASSP, EUSIPCO). The expected total minimum number is 3 journal articles and about 5 conference papers.

C3. *Method and approach*

The team members are

- Bogdan Dumitrescu (BD), project leader.
- Bogdan Sicleru (BS), currently PhD student of BD (started PhD in Oct.2008, but collaborated also earlier with BD). He should defend his thesis at the end of 2011 and he will continue as a post-doc. He will be hired also as an assistant at PUB, if a position will be available in fall 2011, as expected. His thesis topic is optimization with positive polynomials and as such he is acquainted with convex optimization tools and also with filter design. One

of his main contributions is the implementation of the library POS3POLY (www.schur.pub.ro/pos3poly). He has coauthored 2 ISI journal articles, see BD's publication list.

- Cristian Rusu (CR), currently PhD student of BD (started in Oct.2009), is expected to finish his thesis at the end of 2012. Then, he will be replaced with a new PhD student (the aim is to recruit a master student already this year and introduce him/her to the topics of this project). CR's thesis subject is dictionary optimization for sparse representations.

BS and CR will work full time for the project (they have no other research projects and their teaching duties will be minimal), while BD will work about 30-40% of his time for this project.

The work at this project requires moderate computer power, as given by a standard desktop computer, and documentation. The distributed algorithms implied by **O3** can be simulated on a single computer, since they are organized iteratively and their complexity is mainly given by the number of global iterations (the local duration of an iteration step being roughly the same for all processors).

The research will be carried out in a standard way, based on

1. Documentation of state-of-the art literature, including implementations of best algorithms, if they are not already publicly available.
2. Innovation, based on different approaches to the studied problems.
3. Test implementations, mainly in Matlab, but also in C if the need of reducing the running time arises (possible for **O4**), for checking if the new algorithms compete well with the available ones and for finding good values of the parameters (if any).
4. Generalization of approaches that show good behavior, including theoretical foundation.
5. Writing research articles that contain the theoretical results, clear description of the method and sufficient experimental or simulation results.
6. Making public, on www.schur.pub.ro, the code for the most important algorithms, with the aim of producing reproducible research.

A tentative schedule of the activity is presented in the tables below. As supervisor, BD will participate at all activities (more at documentation, generating new ideas and writing, less at actual implementation); the tables give only the tasks of BS and CR (including his successor). The notation Ox.y refers to objective Ox, activity y (a number from 1 to 6, as given above); since innovation is hard to schedule, it is not mentioned explicitly. The objectives **O1** and **O4** are planned for the first year, as **O1** is simpler and **O4** has been already started by CR, whose thesis should be ready at the end of 2012. The objectives **O2** and **O3** are planned for the next two years. The publication submissions are planned for the summer trimester, when there is more time for writing long papers and taking into account that the ICASSP deadline is usually in September; this would make 3 journal papers and 3 conference papers; other papers will be written as the opportunity occurs; this is hard to plan.

The partial objectives after the second year are: for **O2**, the study and comparison of greedy algorithms (the third year being dedicated to a more general study, oriented on a comparison with the sparse least-squares and regularized problems); for **O3**, the study of greedy algorithms for distributed filtering (in the third year, extension to convex relaxation and possibly other techniques will be studied).

The task assignment shown in the tables is the initial one. As the progress on all topics will be discussed in periodical team meetings, each team member will be able to contribute to any theme and, if the ideas look valuable, he will be allocated time for testing them. Besides the research tasks, BS will act as webmaster.

	Oct. – Dec. 2011	Jan. – Mar. 2012	Apr. – June 2012	July – Sep. 2012
BS	O1.1	O1.3	O1.3, O1.4	O1.5, O1.6
CR	O4.1	O4.3	O4.3	O4.5, O4.6

	Oct. – Dec. 2012	Jan. – Mar. 2013	Apr. – June 2013	July – Sep. 2013
BS	O2.1	O2.1, O2.3	O2.3	O2.3, O2.5, O2.6
CR	O3.1	O3.1, O3.3	O3.3	O3.3, O3.5

	Oct. – Dec. 2013	Jan. – Mar. 2014	Apr. – June 2014	July – Sep. 2014
BS	O2.3, O2.4	O2.3, O2.4	O2.5	O1-4.6
CR	O3.3	O3.3, O3.4	O3.3, O3.4, O3.5	O3.5, O3.6

C4. ***Impact, relevance, applications***

The planned impact is mostly on the theoretical level, the foreseen results of this project consisting of new algorithms and descriptions of their properties and behavior. Since our purpose is to obtain algorithms that are better than those currently available or are completely new, we expect publications in top international journals like IEEE Transactions on Signal Processing, IEEE Signal Processing Letters or Signal Processing. Due to maximum visibility, we expect also a reasonable number of citations.

The objective **O4** can have an applicative impact, as it concerns classification of audio material. Also, advances on the use of sparse predictor may benefit other audio signals tasks, such as coding. The other objectives can also produce results that are useful in applications (sparse filters implementation, filtering algorithms).

The chosen research topics are relevant for the current interests in signal processing research; as an illustration, the word “sparse” appears in 69 papers accepted at ICASSP 2011; however, our objectives cover less explored areas and hence have high potential relevance if our research is successful, by bringing novelty in a “hot” field.

C5. ***Resources and budget***

The research will be carried out in the Faculty of Automatic Control and Computers, room ED206, where there is space for 5-6 persons. The basic furniture and equipments are already there, including printers, scanner, copying machine, video projector; however, the computers are 3-6 years old and some do not have the computing power necessary for the amount of computation require by this project. The room is currently used by the members of this research team and by consulting professors Corneliu Popeea and Boris Jora (whose expertise is always valuable, although they are not expected to work directly at this project; since they retired, they spend relatively few time at the university).

The projected expenses are split as follows.

Salaries go mainly to the younger members of the team. The following figures represent employer's expenses: 1000 lei means a salary of about 776 lei before taxes and about 575 lei after taxes, see www.calculatorsalariu.ro)

Bogdan Dumitrescu (part time, professor): 3000 lei/month

Bogdan Sicleru (full time, mostly as a post-doc): 5000 lei/month

Cristian Rusu (full time, PhD student): 3500 lei/month

Total salary expenses: 11500 lei/month.

Inventory expenses are as follows:

a. Computers.

- 4-5 desktop computers for the team members and master students who will have research work related to the project and will be temporarily hosted by the team: 20000 lei
- 2 laptops: 12000 lei

b. Consumables: 8000 lei

c. Other expenses like IEEE member fees (for getting lower registration fees at IEEE conferences), possible expenses with extra pages at IEEE journals: 5000 lei

d. Reserve for unforeseen situations: 5000 lei.

Mobilities. We plan to participate at 2-3 top conferences (like ICASSP, EUSIPCO and possibly dedicated workshops) each year (about 8000 lei/conference in average). The rest of the money will be used for short or longer research stages (stages of 2-3 months will be given only to the junior members of the team). The most probable destination of the research stages is Tampere University of Technology, but alternatives will be actively sought.

Overhead: 25% of the salaries.

Budget Breakdown (lei)

Budget chapter (expenses)	2011 (lei)	2012 (lei)	2013 (lei)	2014 (lei)	Total (lei)
Salaries	34500	138000	138000	103500	414000
Inventory	0	35000	10000	5000	50000
Mobility	0	35000	35000	30000	100000
Overhead	8625	34500	34500	25875	103500
Total	43125	242500	217500	164375	667500

Budget Breakdown (euro; 1 euro=4.3 lei)

Budget chapter (expenses)	Total (euro)
Salaries	96279
Inventory	11627
Mobility	23256
Overhead	24070
Total	155232

The information in this application is hereby certified to be correct.

Project leader,

Last name, first name: DUMITRESCU, Bogdan

Signature: B Dit

Date: May 4, 2011

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