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Université Rennes 1

Activity Report 2015

Project-Team PANAMA

Parcimonie et Nouveaux Algorithmes pour le Signal et la Modélisation Audio

IN COLLABORATION WITH: Institut de recherche en informatique et systèmes aléatoires (IRISA)

RESEARCH CENTER Rennes - Bretagne-Atlantique

THEME Language, Speech and Audio

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Project-Team PANAMA

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Keywords:

Computer Science and Digital Science:

- 1.2.6. Sensor networks
- 3.1.1. Modeling, representation
- 3.3.3. Big data analysis
- 3.4.1. Supervised learning
- 3.4.2. Unsupervised learning
- 3.4.4. Optimization and learning
- 3.4.5. Bayesian methods
- 3.4.6. Neural networks
- 3.4.7. Kernel methods
- 3.4.8. Deep learning
- 3.5.1. Analysis of large graphs
- 5.10.2. Perception
- 5.11.2. Home/building control and interaction
- 5.3.2. Sparse modeling and image representation
- 5.7.1. Sound
- 5.7.2. Music
- 5.7.3. Speech
- 5.7.4. Analysis
- 5.9.1. Sampling, acquisition
- 5.9.2. Estimation, modeling
- 5.9.3. Reconstruction, enhancement
- 5.9.4. Signal processing over graphs
- 5.9.5. Sparsity-aware processing
- 5.9.6. Optimization tools
- 6.1.4. Multiscale modeling
- 6.2.5. Numerical Linear Algebra
- 6.2.6. Optimization
- 6.3.1. Inverse problems
- 6.3.2. Data assimilation
- 7.8. Information theory
- 7.9. Graph theory

Other Research Topics and Application Domains:

- 1.3. Neuroscience and cognitive science
- 2.5.1. Sensorimotor disabilities
- 2.6. Biological and medical imaging
- 5.6. Robotic systems
- 5.8. Learning and training

- 6.3.3. Network services
- 8.1.2. Sensor networks for smart buildings
- 8.4. Security and personal assistance
- 9.1. Education
- 9.2.1. Music, sound
- 9.2.2. Cinema, Television
- 9.2.3. Video games
- 9.6. Reproducibility
- 9.9.1. Environmental risks

1. Members

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2. Overall Objectives

2.1. Overall positioning

At the interface between audio modeling and mathematical signal processing, the global objective of PANAMA is to develop mathematically founded and algorithmically efficient techniques to model, acquire and process high-dimensional signals, with a strong emphasis on acoustic data.

Applications fuel the proposed mathematical and statistical frameworks with practical scenarii, and the developed algorithms are extensively tested on targeted applications. PANAMA's methodology relies on a closed loop between theoretical investigations, algorithmic development and empirical studies.

2.2. Scientific foundations

The scientific foundations of PANAMA are focused on sparse representations and probabilistic modeling, and its scientific scope is extended in three major directions:

- The extension of the sparse representation paradigm towards that of "sparse modeling", with the challenge of establishing, strengthening and clarifying connections between sparse representations and machine learning.
- A focus on sophisticated probabilistic models and advanced statistical methods to account for complex dependencies between multi-layered variables (such as in audio-visual streams, musical contents, biomedical data ...).
- The investigation of graph-based representations, processing and transforms, with the goal to describe, model and infer underlying structures within content streams or data sets.

2.3. Applications

The main industrial sectors in relation with the topics of the PANAMA research group are the telecommunication sector, the Internet and multimedia sector, the musical and audiovisual production sector and, marginally, the sector of education and entertainment. Source separation is one of PANAMA's major applicative focus generating increasing industrial transfers. The models, methods and algorithms developed in the team have many potential applications beyond audio processing and modeling – the central theme of the PANAMA project-team – in particular to biomedical signals. Such applications are primarily investigated in partnership with research groups with the relevant expertise (within or outside Inria).

On a regular basis, PANAMA is involved in bilateral or multilateral partnerships, within the framework of consortia, networks, thematic groups, national and European research projects, as well as industrial contracts with various local companies.

3. Research Program

3.1. Axis 1: sparse models and representations

3.1.1. Efficient sparse models and dictionary design for large-scale data

Sparse models are at the core of many research domains where the large amount and high-dimensionality of digital data requires concise data descriptions for efficient information processing. Recent breakthroughs have demonstrated the ability of these models to provide concise descriptions of complex data collections, together with algorithms of provable performance and bounded complexity.

A crucial prerequisite for the success of today's methods is the knowledge of a "dictionary" characterizing how to concisely describe the data of interest. Choosing a dictionary is currently something of an "art", relying on expert knowledge and heuristics.

Pre-chosen dictionaries such as wavelets, curvelets or Gabor dictionaries, are based upon stylized signal models and benefit from fast transform algorithms, but they fail to fully describe the content of natural signals and their variability. They do not address the huge diversity underlying modern data much beyond time series and images: data defined on graphs (social networks, internet routing, brain connectivity), vector valued data (diffusion tensor imaging of the brain), multichannel or multi-stream data (audiovisual streams, surveillance networks, multimodal biomedical monitoring).

The alternative to a pre-chosen dictionary is a trained dictionary learned from signal instances. While such representations exhibit good performance on small-scale problems, they are currently limited to low dimensional signal processing due to the necessary training data, memory requirements and computational complexity. Whether designed or learned from a training corpus, dictionary-based sparse models and the associated methodology fail to scale up to the volume and resolution of modern digital data, for they intrinsically involve difficult linear inverse problems. To overcome this bottleneck, a new generation of efficient sparse models is needed, beyond dictionaries, encompassing the ability to provide sparse and structured data representations as well as computational efficiency. For example, while dictionaries describe low-dimensional signal models in terms of their "synthesis" using few elementary building blocks called atoms, in "analysis" alternatives the low-dimensional structure of the signal is rather "carved out" by a set of equations satisfied by the signal. Linear as well as nonlinear models can be envisioned.

3.1.2. Compressive Learning

A flagship emerging application of sparsity is the paradigm of compressive sensing, which exploits sparse models at the analog and digital levels for the acquisition, compression and transmission of data using limited resources (fewer/less expensive sensors, limited energy consumption and transmission bandwidth, etc.). Besides sparsity, a key pillar of compressive sensing is the use of random low-dimensional projections. Through compressive sensing, random projections have shown their potential to allow drastic dimension reduction with controlled information loss, provided that the projected signal vector admits a sparse representation in some transformed domain. A related scientific domain, where sparsity has been recognized as a key enabling factor, is Machine Learning, where the overall goal is to design statistically founded principles and efficient algorithms in order to infer general properties of large data collections through the observation of a limited number of representative examples. Marrying sparsity and random low-dimensional projections with machine learning shall allow the development of techniques able to efficiently capture and process the information content of large data collections. The expected outcome is a dramatic increase of the impact of sparse models in machine learning, as well as an integrated framework from the signal level (signals and their acquisition) to the semantic level (information and its manipulation), and applications to data sizes and volumes of collections that cannot be handled by current technologies.

3.2. Axis 2: robust acoustic scene analysis

3.2.1. Compressive acquisition and processing of acoustic scenes

Acoustic imaging and scene analysis involve acquiring the information content from acoustic fields with a limited number of acoustic sensors. A full 3D+t field at CD quality and Nyquist spatial sampling represents roughly 10^6 microphones/ m^3 . Dealing with such high-dimensional data requires to drastically reduce the data flow by positioning appropriate sensors, and selecting from all spatial locations the few spots where acoustic sources are active. The main goal is to develop a theoretical and practical understanding of the conditions under which compressive acoustic sensing is both feasible and robust to inaccurate modeling, noisy measures, and partially failing or uncalibrated sensing devices, in various acoustic sensing scenarii. This requires the development of adequate algorithmic tools, numerical simulations, and experimental data in simple settings where hardware prototypes can be implemented.

3.2.2. Robust audio source separation

Audio signal separation consists in extracting the individual sound of different instruments or speakers that were mixed on a recording. It is now successfully addressed in the academic setting of linear instantaneous mixtures. Yet, real-life recordings, generally associated to reverberant environments, remain an unsolved difficult challenge, especially with many sources and few audio channels. Much of the difficulty comes from the combination of (i) complex source characteristics, (ii) sophisticated underlying mixing model and (iii) adverse recording environments. Moreover, as opposed to the "academic" blind source separation task, most applicative contexts and new interaction paradigms offer a variety of situations in which prior knowledge and adequate interfaces enable the design and the use of informed and/or manually assisted source separation methods.

The former METISS team has developed a generic and flexible probabilistic audio source separation framework that has the ability to combine various acoustic models such as spatial and spectral source models. A first objective is to instantiate and validate specific instances of this framework targeted to real-world industrial applications, such as 5.1 movie re-mastering, interactive music soloist control and outdoor speech enhancement. Extensions of the framework are needed to achieve real-time online processing, and advanced constraints or probabilistic priors for the sources at hand need to be designed, while paying attention to computational scalability issues.

In parallel to these efforts, expected progress in sparse modeling for inverse problems shall bring new approaches to source separation and modeling, as well as to source localization, which is often an important first step in a source separation workflow. In particular, a research avenue consists in investigating physically motivated, lower-level source models, notably through sparse analysis of sound waves. This should be complementary with the modeling of non-point sources and sensors, and a widening of the notion of "source localization" to the case of extended sources (i.e., considering problems such as the identification of the directivity of the source as well as its spatial position), with a focus on boundary conditions identification. A general perspective is to investigate the relations between the physical structure of the source and the particular structures that can be discovered or enforced in the representations and models used for characterization, localization and separation.

3.3. Axis 3: large-scale audio content processing and self-organization

3.3.1. Motif discovery in audio data

Facing the ever-growing quantity of multimedia content, the topic of motif discovery and mining has become an emerging trend in multimedia data processing with the ultimate goal of developing weakly supervised paradigms for content-based analysis and indexing. In this context, speech, audio and music content, offers a particularly relevant information stream from which meaningful information can be extracted to create some form of "audio icons" (key-sounds, jingles, recurrent locutions, musical choruses, etc ...) without resorting to comprehensive inventories of expected patterns.

This challenge raises several fundamental questions that will be among our core preoccupations over the next few years. The first question is the deployment of motif discovery on a large scale, a task that requires extending audio motif discovery approaches to incorporate efficient time series pattern matching methods (fingerprinting, similarity search indexing algorithms, stochastic modeling, etc.). The second question is that of the use and interpretation of the motifs discovered. Linking motif discovery and symbolic learning techniques, exploiting motif discovery in machine learning are key research directions to enable the interpretation of recurring motifs.

On the application side, several use cases can be envisioned which will benefit from motif discovery deployed on a large scale. For example, in spoken content, word-like repeating fragments can be used for several spoken document-processing tasks such as language-independent topic segmentation or summarization. Recurring motifs can also be used for audio summarization of audio content. More fundamentally, motif discovery paves the way for a shift from supervised learning approaches for content description to unsupervised paradigms where concepts emerge from the data.

3.3.2. Structure modeling and inference in audio and musical contents

Structuring information is a key step for the efficient description and learning of all types of contents, and in particular audio and musical contents. Indeed, structure modeling and inference can be understood as the task of detecting dependencies (and thus establishing relationships) between different fragments, parts or sections of information content.

A stake of structure modeling is to enable more robust descriptions of the properties of the content and better model generalization abilities that can be inferred from a particular content, for instance via cache models, trigger models or more general graphical models designed to render the information gained from structural inference. Moreover, the structure itself can become a robust descriptor of the content, which is likely to be more resistant than surface information to a number of operations such as transmission, transduction, copyright infringement or illegal use.

In this context, information theory concepts need to be investigated to provide criteria and paradigms for detecting and modeling structural properties of audio contents, covering potentially a wide range of application domains in speech content mining, music modeling or audio scene monitoring.

4. Application Domains

4.1. Acoustic scene capture

Acoustic fields carry much information about audio sources (musical instruments, speakers, etc.) and their environment (e.g., church acoustics differ much from office room acoustics). A particular challenge is to capture as much information from a complete 3D+t acoustic field associated with an audio scene, using as few sensors as possible. The feasibility of compressive sensing to address this challenge was shown in certain scenarii, and the actual implementation of this framework will potentially impact practical scenarii such as remote surveillance to detect abnormal events, e.g. for health care of the elderly or public transport surveillance.

4.2. Audio signal separation in reverberant environments

Audio signal separation consists in extracting the individual sound of different instruments or speakers that were mixed on a recording. It is now successfully addressed in the academic setting of linear instantaneous mixtures. Yet, real-life recordings, generally associated to reverberant environments, remain an unsolved difficult challenge, especially with many sources and few audio channels. Much of the difficulty comes from the estimation of the unknown room impulse response associated to a matrix of mixing filters, which can be expressed as a dictionary-learning problem. Solutions to this problem have the potential to impact, for example, the music and game industry, through the development of new digital re-mastering techniques and virtual reality tools, but also surveillance and monitoring applications, where localizing audio sources is important.

4.3. Multimedia indexing

Audiovisual and multimedia content generate large data streams (audio, video, associated data such as text, etc.). Manipulating large databases of such content requires efficient techniques to: segment the streams into coherent sequences; label them according to words, language, speaker identity, and more generally to the type of content; index them for easy querying and retrieval, etc. As the next generation of online search engines will need to offer content-based means of searching, the need to drastically reduce the computational burden of these tasks is becoming all the more important as we can envision the end of the era of wasteful datacenters that can increase forever their energy consumption. Most of today's techniques to deal with such large audio streams involve extracting features such as Mel Frequency Cepstral Coefficients (MFCC) and learning high-dimensional statistical models such as Gaussian Mixture Models, with several thousand parameters. The

exploration of a compressive learning framework is expected to contribute to new techniques to efficiently process such streams and perform segmentation, classification, etc., in the compressed domain. A particular challenge is to understand how this paradigm can help exploiting truly multimedia features, which combine information from different associated streams such as audio and video, for joint audiovisual processing.

4.4. Brain source imaging

Epilepsies constitute a common neurological disorder that affects about 1% of the world population. As the epileptic seizure is a dynamic phenomenon, imaging techniques showing static images of the brain (MRI, PET scan) are frequently not the best tools to identify the brain area of interest. Electroencephalography (EEG) is the technique most indicated to capture transient events directly related to the underlying epileptic pathology (like interictal spikes, in particular). EEG convey essential information regarding brain (patho)physiological activity. In addition, recording techniques of surface signals have the major advantage of being noninvasive. For this reason, an increased use in the context of epilepsy surgery is most wanted. However, to reach this objective, we have to solve an electromagnetic inverse problem, that is to say to estimate the current generators underlying noisy EEG data. Theoretically, a specific electromagnetic field pattern may be generated by an infinite number of current distributions. The considered inverse problem, called "brain source imaging problem", is then said to be ill-posed.

5. Highlights of the Year

5.1. Highlights of the Year

5.1.1. Awards

Srdan Kitic won the CONEXANT award for best student paper on audio signal processing at LVA/ICA'2015 conference .

BEST PAPER AWARD:

[31]

S. KITIĆ, N. BERTIN, R. GRIBONVAL. *Sparsity and cosparsity for audio declipping: a flexible non-convex approach*, in "LVA/ICA 2015 - The 12th International Conference on Latent Variable Analysis and Signal Separation", Liberec, Czech Republic, August 2015, 8 p., https://hal.inria.fr/hal-01159700

6. New Software and Platforms

6.1. FASST2

Flexible Audio Source Separation Toolbox KEYWORDS: Audio - Source Separation SCIENTIFIC DESCRIPTION

Only source separation software publicly available allowing to use both spacial and spectral source properties with a generalised EM algorithm (expectation - maximisation). Fast specification of each use case by the choice of suitable constraints in constraint libraries.

FUNCTIONAL DESCRIPTION

Toolbox for the fast design of audio source separation adapted to any use case.

- Participants: Emmanuel Vincent and Yann Salaun
- Contact: Emmanuel Vincent
- URL: http://fasst.gforge.inria.fr

6.2. Multi-channel BSS Locate Basic

KEYWORDS: Audio - Localization - Signal processing - Multichannel signal SCIENTIFIC DESCRIPTION

Multi-Channel BSS Locate is a Matlab toolbox to estimate Direction Of Arrival (expressed both in azimuth and elevation) of multiple sources in a multi-channel audio signal recorded by an array of microphones. This toolbox implements the previous 8 angular spectrum methods presented in BSS Locate (GCC-PHAT, GCC-NONLIN, MUSIC and several SNR-based spectra).

- Authors: Emmanuel Vincent, Charles Blandin, Alexey Ozerov, Ewen Camberlein, Romain Lebarbenchon, Frédéric Bimbot and Nancy Bertin
- Contact: Emmanuel Vincent
- URL: http://bass-db.gforge.inria.fr/bss_locate/

6.3. SPADE

Sparse Audio Declipper KEYWORDS: Audio - Sparse regularization - Declipping FUNCTIONAL DESCRIPTION

Matlab routines to reproduce audio declipping experiments from the papers:

- Srdan Kitic, Nancy Bertin, Remi Gribonval. Audio Declipping by Cosparse Hard Thresholding. iTwist - 2nd international - Traveling Workshop on Interactions between Sparse models and Technology, Aug 2014, Namur, Belgium. [95]
- Srdan Kitic, Nancy Bertin, Remi Gribonval. Sparsity and cosparsity for audio declipping: a flexible non-convex approach. LVA/ICA 2015 The 12th International Conference on Latent Variable Analysis and Signal Separation, Aug 2015, Liberec, Czech Republic. pp.8. [31]
- Participants: Srdan Kitic, Nancy Bertin and Rémi Gribonval
- Contact: Rémi Gribonval
- URL: http://xspaad.gforge.inria.fr/

7. New Results

7.1. Recent results on sparse representations

Sparse approximation, high dimension, scalable algorithms, dictionary design, sample complexity

The team has had a substantial activity ranging from theoretical results to algorithmic design and software contributions in the field of sparse representations, which is at the core of the ERC project PLEASE (projections, Learning and Sparsity for Efficient Data Processing, see Section 9.2.1.1).

7.1.1. Theoretical results on sparse representations, graph signal processing, and dimension reduction

Participants: Rémi Gribonval, Yann Traonmilin, Gilles Puy, Nicolas Tremblay, Pierre Vandergheynst.

Main collaboration: Mike Davies (University of Edinburgh), Pierre Borgnat (ENS Lyon),

Stable recovery of low-dimensional cones in Hilbert spaces: Many inverse problems in signal processing deal with the robust estimation of unknown data from underdetermined linear observations. Low dimensional models, when combined with appropriate regularizers, have been shown to be efficient at performing this task. Sparse models with the ℓ_1 -norm or low rank models with the nuclear norm are examples of such successful combinations. Stable recovery guarantees in these settings have been established using a common tool adapted to each case: the notion of restricted isometry property (RIP). This year, we established generic RIP-based guarantees for the stable recovery of cones (positively homogeneous model sets) with arbitrary regularizers. These guarantees were illustrated on selected examples. For block structured sparsity in the infinite dimensional setting, we used the guarantees for a family of regularizers which efficiency in terms of RIP constant can be controlled, leading to stronger and sharper guarantees than the state of the art. A journal paper is currently under revision [57].

Recipes for stable linear embeddings from Hilbert spaces to \mathbb{R}^m : We considered the problem of constructing a linear map from a Hilbert space (possibly infinite dimensional) to \mathbb{R}^m that satisfies a restricted isometry property (RIP) on an arbitrary signal model set. We obtained a generic framework that handles a large class of low-dimensional subsets but also *unstructured* and *structured* linear maps. We provided a simple recipe to prove that a random linear map satisfies a general RIP on the model set with high probability. We also described a generic technique to construct linear maps that satisfy the RIP. Finally, we detailed how to use our results in several examples, which allow us to recover and extend many known compressive sampling results. This has been presented at the conference EUSIPCO 2015 [28], and a journal paper has been submitted [55].

Random sampling of bandlimited signals on graphs: We studied the problem of sampling k-bandlimited signals on graphs. We proposed two sampling strategies that consist in selecting a small subset of nodes at random. The first strategy is non-adaptive, i.e., independent of the graph structure, and its performance depends on a parameter called the graph coherence. On the contrary, the second strategy is adaptive but yields optimal results. Indeed, no more than O(klog(k)) measurements are sufficient to ensure an accurate and stable recovery of all k-bandlimited signals. This second strategy is based on a careful choice of the sampling distribution, which can be estimated quickly. Then, we proposed a computationally efficient decoder to reconstruct k-bandlimited signals from their samples. We proved that it yields accurate reconstructions and that it is also stable to noise. Finally, we conducted several experiments to test these techniques. A journal paper has been submitted [56].

Accelerated spectral clustering: We leveraged the proposed random sampling technique to propose a faster spectral clustering algorithm. Indeed, classical spectral clustering is based on the computation of the first k eigenvectors of the similarity matrix' Laplacian, whose computation cost, even for sparse matrices, becomes prohibitive for large datasets. We showed that we can estimate the spectral clustering distance matrix without computing these eigenvectors: by graph filtering random signals. Also, we took advantage of the stochasticity of these random vectors to estimate the number of clusters k. We compared our method to classical spectral clustering on synthetic data, and show that it reaches equal performance while being faster by a factor at least two for large datasets. A conference paper has been accepted at ICASSP 2016 [43] and a long version is in preparation.

7.1.2. Algorithmic and theoretical results on dictionary learning

Participants: Rémi Gribonval, Luc Le Magoarou, Nicolas Bellot, Thomas Gautrais, Nancy Bertin, Srdan Kitic.

Main collaboration (theory for dictionary learning): Rodolphe Jenatton, Francis Bach (Equipe-projet SIERRA (Inria, Paris)), Martin Kleinsteuber, Matthias Seibert (TU-Munich),

Theoretical guarantees for dictionary learning : An important practical problem in sparse modeling is to choose the adequate dictionary to model a class of signals or images of interest. While diverse heuristic techniques have been proposed in the litterature to learn a dictionary from a collection of training samples, there are little existing results which provide an adequate mathematical understanding of the behaviour of these techniques and their ability to recover an ideal dictionary from which the training samples may have been generated.

Beyond our pioneering work [86], [109] [5] on this topic, which concentrated on the noiseless case for non-overcomplete dictionaries, we showed the relevance of an ℓ^1 penalized cost function for the locally stable identification of overcomplete incoherent dictionaries, in the presence of noise and outliers [19]. Moreover, we established sample complexity bounds of dictionary learning and other related matrix factorization schemes (including PCA, NMF, structured sparsity ...) [20].

Learning computationally efficient dictionaries Classical dictionary learning is limited to small-scale problems. Inspired by usual fast transforms, we proposed a general dictionary structure that allows cheaper manipulation, and an algorithm to learn such dictionaries –and their fast implementation. The principle and its application to image denoising appeared at ICASSP 2015 [33] and an application to speedup linear inverse problems was published at EUSIPCO 2015 [32]. A journal paper is currently under revision [51].

We further explored the application of this technique to obtain fast approximations of Graph Fourier Transforms – a conference paper on this latter topic has been accepted for publication in ICASSP 2016 [41]. A C++ software library is in preparation to release the resulting algorithms.

Operator learning for cosparse representations: Besides standard dictionary learning, we also considered learning in the context of the cosparse model. The overall problem is to learn a low-dimensional signal model from a collection of training samples. The mainstream approach is to learn an overcomplete dictionary to provide good approximations of the training samples using sparse synthesis coefficients. This famous sparse model has a less well known counterpart, in analysis form, called the cosparse analysis model. In this new model, signals are characterized by their parsimony in a transformed domain using an overcomplete analysis operator.

This year we obtained an upper bound of the sample complexity of the learning process for analysis operators, and designed a stochastic gradient descent (SGD) method to efficiently learn analysis operators with separable structures. Numerical experiments were provided that link the sample complexity to the convergence speed of the SGD algorithm. A journal paper has been published [24].

7.1.3. An alternative framework for sparse representations: analysis sparse models

Participants: Rémi Gribonval, Nancy Bertin, Srdan Kitic, Laurent Albera.

In the past decade there has been a great interest in a synthesis-based model for signals, based on sparse and redundant representations. Such a model assumes that the signal of interest can be composed as a linear combination of *few* columns from a given matrix (the dictionary). An alternative *analysis-based* model can be envisioned, where an analysis operator multiplies the signal, leading to a *cosparse* outcome. Building on our pioneering work on the cosparse model [101], [85], [102] successful applications of this approach to sound source localization, audio declipping and brain imaging have been developed this year.

Versatile co-sparse regularization: Digging the groove of last year results (comparison of the performance of several cosparse recovery algorithms in the context of sound source localization [94], demonstration of its efficiency in situations where usual methods fail ([96], see paragraph 7.5.2), applicability to the hard declipping problem [95], application to EEG brain imaging [60] (see paragraph 7.5.3), a journal paper embedding the latest algorithms and results in sound source localization and brain source localization in a unified fashion was published in IEEE Transactions on Signal Processing [23]. Other communications were made in conferences and workshops [50], [31] and Srdan Kitic defended his PhD thesis [12]. New results include experimental confirmation of robustness and versatility of the proposed scheme, and of its computational merits (convergence speed increasing with the amount of data)

Parametric operator learning for cosparse calibration: In many inverse problems, a key challenge is to cope with unknown physical parameters of the problem such as the speed of sound or the boundary impedance. In the sound source localization problem, we showed that the unknown speed of sound can be learned jointly in the process of cosparse recovery, under mild conditions (work presented last year at iTwist'14 workshop [66]). This year, improved and extended results were obtained: first with a new algorithm for sound source localization with unknown speed of sound [12], then by extending the formulation to the case of unknown boundary impedance, and showing that a similar biconvex formulation and optimization could solve this new problem efficiently (conference paper accepted for publication in ICASSP 2016 [38], see also Section 7.3.2).

7.2. Activities on waveform design for telecommunications

Peak to Average Power Ratio (PAPR), Orthogonal Frequency Division Multiplexing (OFDM), Generalized Waveforms for Multi Carrier (GWMC)

7.2.1. Characterizing multi-carrier waveform systems with optimum PAPR Participant: Rémi Gribonval.

Main collaboration: Marwa Chafii, Jacques Palicot, Carlos Bader (Equipe SCEE, Supelec, Rennes)

In the context of the TEPN (Towards Energy Proportional Networks) Comin Labs project (see Section 9.1.1.2), in collaboration with the SCEE team at Supelec (thesis of Marwa Chafii co-supervised by R. Gribonval), we investigated a problem related to dictionary design: the characterization of waveforms with low Peak to Average Power Ratio (PAPR) for wireless communications. This is motivated by the importance of a low PAPR for energy-efficient transmission systems. A first stage of the work consisted in characterizing the statistical distribution of the PAPR for a general family of multi-carrier systems, leading to a journal paper [77] and several conference communications [75], [76]. The work this year concentrated on characterizing waveforms with optimum PAPR [30], [48].

7.3. Emerging activities on compressive learning and inverse problems

Compressive sensing, compressive learning, audio inpainting,

7.3.1. Audio inpainting

Participants: Rémi Gribonval, Nancy Bertin, Srdan Kitic.

Inpainting is a particular kind of inverse problems that has been extensively addressed in the recent years in the field of image processing.

Building upon our previous pioneering contributions (definition of the audio inpainting problem as a general framework for many audio processing tasks, application to the audio declipping or desaturation problem, formulation as a sparse recovery problem [59]), new results were obtained last year and this year to address the case of audio declipping with the competitive cosparse approach. Last year, its promising results, especially when the clipping level is low, were confirmed experimentally by the formulation and use of a new algorithm named Cosparse Iterative Hard Tresholding [95], which is a counterpart of the sparse Consistent Iterative Hard Thresholding.

This year, we proposed a new algorithmic framework called SPADE, based on non-convex heuristics and which can accomodate both the sparse and cosparse prior. We studied their performance numerically and observed in particular that its cosparse version offers a very appealing trade-off between reconstruction performance and computational time [31], making it suitable for practical applications, even in real-time. We could also confirm our results by subjective listening tests conducted this year [12].

The work on cosparse audio declipping was awarded the Conexant best paper award at the LVA/ICA conference [31] and draw the attention of a world leading company in professional audio signal processing, with which some transfer has been negotiated.

Current and future works deal with developing advanced (co)sparse decomposition for audio inpainting, including several forms of structured sparsity (*e.g.* temporal and multichannel joint-sparsity), dictionary learning for inpainting, and several applicative scenarios (declipping, time-frequency inpainting, joint source separation and declipping).

7.3.2. Blind Calibration of Impedance and Geometry

Participants: Rémi Gribonval, Nancy Bertin, Srdan Kitic.

Main collaborations: Laurent Daudet, Thibault Nowakowski, Julien de Rosny (Institut Langevin)

This year, we also investigated extended inverse problem scenarios where a "lack of calibration" may occur, i.e., when some physical parameters are needed for reconstruction but apriori unknown: speed of sound, impedance at the boundaries of the domain where the studied phenomenon propagates, or even the shape of these boundaries. In a first approach, based on our physics-driven cosparse regularization of the sound source localization problem [23] (see section 7.1.3), we managed to preserve the sound source localization performance when the speed of sound is unknown, or, equally, when the impedance is unknown, provided the shape is and under some smoothness assumptions. Unlike the previous case (gain calibration), the arising problems are not convex but biconvex, and can be solved with proper biconvex formulation of ADMM algorithm. In a second approach based on eigenmode decomposition (limited to a 2D membrane), we showed that impedance learning with known shape, or shape learning with known impedance can be expressed as two facets of the same problem, and solved by the same approach, from a small number of measurements. Two papers presenting these two sets of results were accepted for publication in ICASSP 2016 [38], [35].

7.3.3. Sketching for Large-Scale Mixture Estimation

Participants: Rémi Gribonval, Nicolas Keriven.

Main collaborations: Patrick Perez (Technicolor R&I France) Anthony Bourrier (formerly Technicolor R&I France, now at GIPSA-Lab)

When fitting a probability model to voluminous data, memory and computational time can become prohibitive. In this work, we propose a framework aimed at fitting a mixture of isotropic Gaussians to data vectors by computing a low-dimensional sketch of the data. The sketch represents empirical moments of the underlying probability distribution. Deriving a reconstruction algorithm by analogy with compressive sensing, we experimentally show that it is possible to precisely estimate the mixture parameters provided that the sketch is large enough. Our algorithm provides good reconstruction and scales to higher dimensions than previous probability mixture estimation algorithms, while consuming less memory in the case of numerous data. It also provides a privacy-preserving data analysis tool, since the sketch does not disclose information about individual datum it is based on [70], [68], [69]. This year, we consolidated our extensions to non-isotropic Gaussians, with new algorithms [49] and conducted large-scale experiments demonstrating its potential for speaker verification. A conference paper has been accepted to ICASSP 2016 [40] and a journal version is being finalized.

7.4. Recent results on tensor decompositions

tensor, multiway array, canonical polyadic decomposition, nonnegative tensor factorization

Multi-linear algebra is defined as the algebra of q-way arrays (q > 2), that is, the arrays whose elements are addressed by more than two indices. The first works dates back to Jordan who was interested in simultaneously diagonalizing two matrices at a time [93]. It is noteworthy that such two matrices can be interpreted as both slices of a three-way array and their joint diagonalization can be viewed as Hitchcock's polyadic decomposition [89] of the associated three-way array. Other works followed discussing rank problems related to multi-way structures and properties of multi-way arrays. However, these exercices in multilinear algebra were not linked to real data analysis but stayed within the realm of mathematics. Studying three-way data really started with Tucker's seminal work, which gave birth to the three-mode factor analysis [112]. His model is now often referred to as the Tucker3 model. At the same moment, other authors focused on a particular case of the Tucker3 model, calling it PARAFAC for PARAllel FACtor analysis [88], and on the means to achieve such a decomposition, which will become the famous canonical decomposition [73]. In honor to Hitchcock's pionneer work, we will call it the Canonical Polyadic (CP) decomposition.

Achieving a CP decomposition has been seen first as a mere non-linear least squares problem, with a simple objective criterion. In fact, the objective is a polynomial function of many variables, where some separate. One could think that this kind of objective is easy because smooth, and even infinitely differentiable. But it turns out that things are much more complicated than they may appear to be at first glance. Nevertheless, the Alternating Least Squares (ALS) algorithm has been mostly utilized to address this minimization problem, because of its programming simplicity. This should not hide the inherently complicated theory that lies behind the optimization problem. Moreover, in most of the applications, actual tensors may not exactly satisfy the

expected model, so that the problem is eventually an approximation rather than an exact decomposition. This may result in a slow convergence (or lack of convergence) of iterative algorithms such as the ALS one [97]. Consequently, a new class of efficient algorithms able to take into account the properties of tensors to be decomposed is needed.

7.4.1. CP decomposition of semi-symmetric three-way arrays subject to arbitrary convex constraints

Participant: Laurent Albera.

Main collaborations : Lu Wang (LTSI, France), Amar Kachenoura (LTSI, France), Lotfi Senhadji (LTSI, France), Jean-Christophe Pesquet (LIGM, France)

We addressed the problem of canonical polyadic decomposition of semi-symmetric 3rd order tensors (i.e. joint diagonalization by congruence) subject to arbitrary convex constraints. Sufficient conditions for the existence of a solution were proved. An efficient algorithm based on the Alternating Direction Method of Multipliers (ADMM) was then designed. ADMM provides an elegant approach for handling the additional constraint terms, while taking advantage of the structure of the objective function. Numerical tests on simulated matrices showed the benefits of the proposed method for low signal to noise ratios. Simulations in the context of nuclear magnetic resonance spectroscopy were also provided. This work was presented at the IEEE CAMSAP'15 conference [29].

7.4.2. Joint eigenvalue decomposition of non-defective matrices for the CP decomposition of tensors

Participant: Laurent Albera.

We proposed a fast and efficient Jacobi-like approach named JET (Joint Eigenvalue decomposition based on Triangular matrices) for the Joint EigenValue Decomposition (JEVD) of a set of real or complex non-defective matrices based on the LU factorization of the matrix of eigenvectors [98]. The JEVD can be useful in several contexts such as CP decomposition of tensors [99] and more particularly in Independent Component Analysis (ICA) based on higher order cumulants where it allows us to blindly compute the mixing matrix of sources with kurtosis of different signs. Regarding the proposed JET approach, contrary to classical Jacobi-like JEVD methods, its iterative procedure can be reduced to the search for only one of the two triangular matrices involved in the factorization of the matrix of eigenvectors, hence decreasing the numerical complexity. Two variants of the JET technique, namely JET-U and JET-O, which correspond to the optimization of two different cost functions were described in detail and these were extended to the complex case. Numerical simulations showed that in many practical cases the JET approach provides more accurate estimation of the matrix of eigenvectors than its competitors and that the lowest numerical complexity is consistently achieved by the JET-U algorithm.

7.5. Source separation and localization

Source separation, sparse representations, tensor decompositions, semi-nonnegative independent component analysis, probabilistic model, source localization

Source separation is the task of retrieving the source signals underlying a multichannel mixture signal.

About a decade ago, state-of-the-art approaches consisted of representing the signals in the time-frequency domain and estimating the source coefficients by sparse decomposition in that basis. These approaches rely only on spatial cues, which are often not sufficient to discriminate the sources unambiguously. Over the last years, we proposed a general probabilistic framework for the joint exploitation of spatial and spectral cues [106], which generalizes a number of existing techniques including our former study on spectral GMMs [61]. We showed how it could be used to quickly design new models adapted to the data at hand and estimate its parameters via the EM algorithm, and it became the basis of a large number of works in the field, including our own. In the last years, improvements were obtained through the use of prior knowledge about the source spatial covariance matrices [83], [92], [91], knowledge on the source positions and room characteristics [84],

or a better initialization of parameters thanks to specific source localization techniques [67]. This accumulated progress lead to two main achievements last year: a new version of the Flexible Audio Source Separation Toolbox, fully reimplemented, was released [108] and we published an overview paper on recent and going research along the path of *guided* separation, *i.e.*, techniques and models allowing to incorporate knowledge in the process towards efficient and robust solutions to the audio source separation problem, in a special issue of IEEE Signal Processing Magazine devoted to source separation and its applications [113].

7.5.1. Towards real-world separation and remixing applications

Participants: Nancy Bertin, Frédéric Bimbot, Nathan Souviraà-Labastie, Ewen Camberlein, Romain Lebarbenchon.

Main collaboration: Emmanuel Vincent (EPI PAROLE, Inria Nancy)

While some challenges remain, work from previous years and our review paper on guided source separation [113] highlighted that progress has been made and that audio source separation is closer than ever to successful industrial applications, especially when some knowledge can be incorporated. This was exemplified by the contract with MAIA Studio, which reached its end in December 2014 and showed in particular how user input or side information could raise source separation tools to efficient solutions in real-world applications.

In some applicative contexts of source separation, several mixtures are available which contain similar instances of a given source. We have designed a general multi-channel source separation framework where additional audio references are available for one (or more) source(s) of a given mixture. Each audio reference is another mixture which is supposed to contain at least one source similar to one of the target sources. Deformations between the sources of interest and their references are modeled in a linear manner using a generic formulation. This is done by adding transformation matrices to an excitation-filter model, hence affecting different axes, namely frequency, dictionary component or time. A nonnegative matrix co-factorization algorithm and a generalized expectation-maximization algorithm are used to estimate the parameters of the model. Different model parameterizations and different combinations of algorithms have been tested on music plus voice mixtures guided by music and/or voice references and on professionally-produced music recordings guided by cover references. Our algorithms has provided improvement to the signal-to-distortion ratio (SDR) of the sources with the lowest intensity by 9 to 15 decibels (dB) with respect to the original mixtures [25]. Combining these techniques, with automatic audio motif spotting, we have proposed a new concept called SPORES (for SPOtted Reference based Separation) and applied it to guided separation of audio tracks [13].

This year saw the beginning of a new industrial collaboration, in the context of the VoiceHome project, aiming at another challenging real-world application: natural language dialog in home applications, such as control of domotic and multimedia devices. As a very noisy and reverberant environment, home is a particularly challenging target for source separation, used here as a pre-processing for speech recognition (and possibly with stronger interactions with voice activity detection or speaker identification tasks as well). In 2015, we participated in a data collection campaign, and in benchmarking and adaptation of existing localization and separation tools to the particular context of this application.

7.5.2. Implicit localization through audio-based control for robotics

Participant: Nancy Bertin.

Main collaborations (audio-based control for robotics): Aly Magassouba and François Chaumette (Inria, EPI LAGADIC, France)

Acoustic source localization is, in general, the problem of determining the spatial coordinates of one or several sound sources based on microphone recordings. This problem arises in many different fields (speech and sound enhancement, speech recognition, acoustic tomography, robotics, aeroacoustics...) and its resolution, beyond an interest in itself, can also be the key preamble to efficient source separation. Common techniques, including beamforming, only provides the *direction of arrival* of the sound, estimated from the *Time Difference of Arrival (TDOA)* [67]. This year, we have particularly investigated alternative approaches, either where the explicit localization is not needed (audio-based control of a robot) or, on the contrary, where the exact location of the source is needed and/or TDOA is irrelevant (cosparse modeling of the acoustic field, see Section 7.1.3).

In robotics, the use of aural perception has received recently a growing interest but still remains marginal in comparison to vision. Yet audio sensing is a valid alternative or complement to vision in robotics, for instance in homing tasks. Most existing works are based on the relative localization of a defined system with respect to a sound source, and the control scheme is generally designed separately from the localization system.

In contrast, the approach that we started investigating last year focuses on a sensor-based control approach. We proposed a new line of work, by considering the hearing sense as a direct and real-time input of closed loop control scheme for a robotic task. Thus, and unlike most previous works, this approach does not necessitate any explicit source localization: instead of solving the localization problem, we focus on developing an innovative modeling based on sound features. To address this objective, we placed ourselves in the sensor-based control framework, especially visual servoing (VS) that has been widely studied in the past [78].

From now on, we have established an analytical model linking sound features and control input of the robot, defined and analyzed robotic homing tasks involving multiple sound sources, and validated the proposed approach by simulations and experiments with an actual robot. This work is mainly lead by Aly Magassouba, whose Ph.D. is co-supervised by Nancy Bertin and François Chaumette. A conference paper presenting these first results was published this year [34] and another was submitted to ICRA 2016. Future work will include additional real-world experiments with the robot Romeo from Aldebaran Robotics, investigation of new tasks with active sensing strategies, explicit use of echoes and reverberation to increase robustness, and exploration of dense methods (control from raw acoustic signals rather than from acoustic features).

7.5.3. Brain source localization

Participants: Laurent Albera, Srdan Kitic, Nancy Bertin, Rémi Gribonval.

Main collaborations : Hanna Becker (GIPSA & LTSI, France), Pierre Comon (GIPSA, France), Isabelle Merlet (LTSI, France), Fabrice Wendling (LTSI, France)

From tensor to sparse models

The brain source imaging problem has been widely studied during the last decades, giving rise to an impressive number of methods using different priors. Nevertheless, a thorough study of the latter, including especially sparse and tensor-based approaches, is still missing. Consequently, we proposed i) a taxonomy of the methods based on a priori assumptions, ii) a detailed description of representative algorithms, iii) a review of identifiability results and convergence properties of different techniques, and iv) a performance comparison of the selected methods on identical data sets. Our aim was to provide a reference study in the biomedical engineering domain which may also be of interest for other areas such as wireless communications, audio source localization, and image processing where ill-posed linear inverse problems are encountered and to identify promising directions for future research in this area. This work was published in the IEEE Signal Processing Magazine [14].

A sparsity-based approach

Identifying the location and spatial extent of several highly correlated and simultaneously active brain sources from EEG recordings and extracting the corresponding brain signals is a challenging problem. In our comparison of source imaging techniques presented at ICASSP'14 [65], the VB-SCCD algorithm [81], which exploits the sparsity of the variational map of the sources, proved to be a promising approach. We proposed several ways to improve this method. In order to adjust the size of the estimated sources, we added a regularization term that imposes sparsity in the original source domain. Furthermore, we demonstrated the application of ADMM, which permitted to efficiently solve the optimization problem. Finally, we also considered the exploitation of the temporal structure of the data by employing L1,2-norm regularization. The performance of the resulting algorithm, called SISSY, was evaluated based on realistic simulations in comparison to VB-SCCD and several state-of-the-art techniques for extended source localization. This work was partially presented at EUSIPCO'14 [64] and a journal paper is in preparation.

Tensor- and sparsity-based approaches

The separation of EEG sources is a typical application of tensor decompositions in biomedical engineering. The objective of most approaches studied in the literature consists in providing separate spatial maps and time signatures for the identified sources. However, for some applications, a precise localization of each source is required.

To achieve this, a two-step approach was presented at the IEEE EMBC conference [26]. The idea of this approach is to separate the sources using the canonical polyadic decomposition in the first step and to employ the results of the tensor decomposition to estimate distributed sources in the second step, using the SISSY algorithm [64].

Next, we proposed to combine the tensor decomposition and the source localization in a single step [27]. To this end, we directly imposed structural constraints, which are based on a priori information on the possible source locations, on the factor matrix of spatial characteristics. The resulting optimization problem was solved using the alternating direction method of multipliers (ADMM), which was incorporated in the alternating least squares tensor decomposition algorithm. Realistic simulations with epileptic EEG data confirmed that the proposed single-step source localization approach outperformed the previously developed two-step approach.

7.5.4. Independent component analysis

Participant: Laurent Albera.

Main collaboration: Sepideh Hajipour (LTSI & BiSIPL), Isabelle Merlet (LTSI, France), Mohammad Bagher Shamsollahi (BiSIPL, Iran)

Independent Component Analysis (ICA) is a very useful tool to process biomedical signals including EEG data.

We proposed a Jacobi-like Deflationary ICA algorithm, named JDICA. More particularly, while a projectionbased deflation scheme inspired by Delfosse and Loubaton's ICA technique (DelL^{\mathbb{R}}) [80] was used, a Jacobilike optimization strategy was proposed in order to maximize a fourth order cumulant-based contrast built from whitened observations. Experimental results obtained from simulated epileptic data mixed with a real muscular activity and from the comparison in terms of performance and numerical complexity with the FastICA [90], RobustICA [114] and DelL^{\mathbb{R}} algorithms, show that the proposed algorithm offers the best trade-off between performance and numerical complexity. This work was published in the IEEE Signal Processing Letters journal [21].

In addition, we illustrated in the ICA context the interest of being able to solve efficiently the (non-orthogonal) JEVD problem. More particularly, we showed that, when the noise covariance matrix is unknown and the source kurtoses have different signs, the joint diagonalization problem involved in the ICAR method [58] becomes a non-orthogonal JEVD problem. Consequently, by using our JET-U algorithm [98], giving birth to the MICAR-U (Modified ICAR based on JET-U) technique, we then provided a more robust ICA method. The identifiability of the MICAR-U technique was studied and proved under some conditions. Computer results given in the context of brain interfaces showed the better ability of the MICAR-U approach to denoise electrocortical data compared to classical ICA techniques for low signal to noise ratio values. These results were presented in [98].

7.5.5. Semi-nonnegative independent component analysis

Participant: Laurent Albera.

Main collaboration: Lu Wang (LTSI, France), Amar Kachenoura (LTSI, France), Lotfi Senhadji (LTSI, France), Huazhong Shu (LIST, China)

ICA plays also an important role in many other areas including speech and audio [62], [63], [74], [71], radiocommunications [79] and document restoration [111] to cite a few.

For instance in [111], the authors use ICA to restore digital document images in order to improve the text legibility. Indeed, under the statistical independence assumption, authors succeed in separating foreground text and bleed-through/show-through in palimpsest images. Furthermore, authors in [82] use ICA to solve the ambiguity in X-ray images due to multi-object overlappings. They presented a novel object decomposition technique based on multi-energy plane radiographs. This technique selectively enhances an object that is characterized by a specific chemical composition ratio of basis materials while suppressing the other overlapping objects. Besides, in the context of classification of tissues and more particularly of brain tumors [107], ICA is very effective. In fact, it allows for feature extraction from Magnetic Resonance Spectroscopy (MRS) signals, representing them as a linear combination of tissue spectra, which are as independent as possible [110]. Moreover, using the JADE algorithm [72] applied to a mixture of sound waves computed by means of the constant-Q transform (Fourier transform with log-frequency) of a temporal waveform broken up into a set of time segments, the authors of [71] describe trills as a set of note pairs described by their spectra and corresponding time envelopes. In this case, pitch and timing of each note present in the trill can be easily deduced.

All the aforementioned applications show the high efficiency of the ICA and its robustness to the presence of noise. Despite this high efficiency in resolving the proposed applicative problems, authors did not fully exploit properties enjoyed by the mixing matrix such as its nonnegativity. For instance in [82], the thickness of each organ, which stands for the mixing coefficient, is real positive. Furthermore, reflectance indices in [111] for the background, the overwriting and the underwriting, which correspond to the mixing coefficients, are also nonnegative. Regarding tissue classification from MRS data, each observation is a linear combination of independent spectra with positive weights representing concentrations [87]; the mixing matrix is again nonnegative.

By imposing the nonnegativity of the mixing matrix within the ICA process, we showed through computer results that the extraction quality can be improved. Exploiting the nonnegativity property of the mixing matrix during the ICA process gives rise to what we call semi-nonnegative ICA. More particularly, we performed the latter by computing a constrained joint CP decomposition of cumulant arrays of different orders [100] having the nonnegative mixing matrix as loading matrices. After merging the entries of the cumulant arrays in the same third order array, the reformulated problem follows the semi-symmetric semi-nonnegative CP model defined in section 7.4.1. Hence we use the new method described in section 7.4.1 to perform semi-nonnegative ICA. Performance results in biomedical engineering were given in the paper cited in section 7.4.1.

7.6. Audio and speech content processing

Audio segmentation, speech recognition, motif discovery, audio mining

7.6.1. Audio motif discovery and spotting

Participants: Frédéric Bimbot, Nathan Souviraà-Labastie.

This work was performed in close collaboration with Emmanuel Vincent from Inria Nancy-Grand Est.

As an alternative to supervised approaches for multimedia content analysis, where predefined concepts are searched for in the data, we investigate content discovery approaches where knowledge emerge from the data. Following this general philosophy, we pursued work on motif discovery in audio contents.

Audio motif discovery is the task of finding out, without any prior knowledge, all pieces of signals that repeat, eventually allowing variability. The developed algorithms allows discovering and collecting occurrences of repeating patterns in the absence of prior acoustic and linguistic knowledge, or training material. When the audio pattern is determined in a user supervised fashion, the task becomes that of motif spotting.

Investigated in the context of SPORES (SPOtted Reference based Separation) [13], audio motif spotting has been illustrated as a useful way to exploit redundancy in audio contents, for guided source separation purposes.

7.6.2. Mobile device for the assistance of users in potentially dangerous situations

Participants: Romain Lebarbenchon, Ewen Camberlein, Frédéric Bimbot.

The S-Pod project is a cooperative project between industry and academia aiming at the development of mobile systems for the detection of potentially dangerous situations in the immediate environment of a user, without requiring his/her active intervention.

In this context, the PANAMA research group has been involved in the design of algorithms for the analysis and monitoring of the acoustic scene around the user, yielding audio-based information which can be fused with other sensors (physiological, positional, etc.) in order to trigger an alarm (and subsequent appropriate measures) when needed.

The last phase of the project has been dedicated towards robustness improvement of audio scene analysis, with a particular focus on threat vs non-threat detection, on the basis of adaptive training scenarii. Knowledge and know-how transfer has been achieved for the hardware implementation of the designed methods and the efficient integration into an operational prototype.

7.7. Music Content Processing and Music Information Retrieval

Acoustic modeling, non-negative matrix factorisation, music language modeling, music structure

7.7.1. Music structure modeling by System & Contrast

Participants: Frédéric Bimbot, Corentin Louboutin.

The *System & Contrast* (S&C) model aims at describing the inner organization of structural segments within music pieces in terms of : (i) a carrier system, i.e. a sequence of morphological elements forming a multidimensional network of self-deducible syntagmatic relationships and (ii) a contrast, i.e. a substitutive element, usually the last one, which partly departs from the logic implied by the rest of the system [16].

With a primary focus on pop music, the S&C model provides a framework to describe internal implication patterns in musical segments by encoding similarities and relations between its constitutive elements so as to minimize the complexity of the resulting description. It is applicable at several timescales and to a wide variety of musical dimensions in a polymorphous way, therefore offering an attractive meta-description of different types of musical contents.

We have established the filiation of the S&C model as an extension of Narmour's Implication-Realization model [104], [105] and Cognitive Rule-Mapping [103].

We have introduced the Minimum Description Length scheme as a productive paradigm that supports the estimation of S&C descriptions and establishes promising connections between Music Data Processing and Information Retrieval on the one hand, and modern theories in Music Perception and Cognition on the other hand, together with interesting perspectives in other areas in Musicology.

The model is currently being investigated for the multi-scale description of chord sequences.

7.7.2. Tree-based representation of music pieces

Participants: Frédéric Bimbot, Corentin Guichaoua.

Modeling music structure, i.e. the organisation of musical elements and their relationships within a piece of music, is an open problem of primary importance in MIR.

To address this challenge, we approach music structure description as the inference of a low complexity generative grammar able to account for the music piece, itself represented as a sequence of symbols.

Originally introduced for the inference of structure in DNA sequences, Straight-Line Grammars (SLG) form a particular subclass of Context-Free Grammars (CFG) which can be used to model symbolic sequences and to represent them as hierarchical trees. However, SLGs appear to be poorly suited to some particularities of musical patterns, such as segmental regularities, closure substitutions and specific style structures.

We are designing and investigating formal and algorithmic extensions of SLGs as SLEGs (Straight-Line Edition Grammars). Based on a more general minimum description criterion, the SLEG extension allows alterations in the generation step and enables the use of priors in the grammar inference process. Current work includes a diagnostic comparison between the various approaches on the structural segmentation of chord sequences from pop songs.

8. Bilateral Contracts and Grants with Industry

8.1. Bilateral Contracts with Industry

8.1.1. Research contract with TDF

Participants: Nancy Bertin, Ewen Camberlein, Rémi Gribonval.

Duration: 6 weeks

Partners: TDF

This contract aimed at conceiving an algorithm to estimate the time offset between to identical or similar audio streams, to implement this algorithm in a prototype and to benchmark it on test files provided by the partner.

8.2. Bilateral Grants with Industry

8.2.1. CIFRE contract with Technicolor R&I France on Very large scale visual comparison Participants: Rémi Gribonval, Himalaya Jain.

Duration: 3 years (2015-2018) Research axis: 3.1.2 Partners: Technicolor R&I France, Inria-Rennes Funding: Technicolor R&I France, ANRT

The grand goal of this thesis is to design, analyze and test new tools to allow large-scale comparison of high-dimensional visual signatures. Leveraging state of the art visual descriptors, the objective is to obtain new compact codes for visual representations, exploiting sparsity and learning, so that they can be stored and compared in an efficient, yet meaningful, way.

9. Partnerships and Cooperations

9.1. National Initiatives

9.1.1. Labex Comin Labs projects

CominLabs is a Laboratoire d'Excellence funded by the PIA (Programme Investissements d'Avenir) in the broad area of telecommunications.

9.1.1.1. HEMISFER

Participant: Rémi Gribonval.

Acronym: HYBRID (Hybrid Eeg-MrI and Simultaneous neuro-feedback for brain Rehabilitation) http://www.hemisfer.cominlabs.ueb.eu/

Research axis: 3.1

CominLabs partners : EPI VISAGES; EPI HYBRID; EPI PANAMA

External partners : EA 4712 team from University of Rennes I; EPI ATHENA, Sophia-Antipolis; Coordinator: Christian Barillot, EPI VISAGES

Description: The goal of HEMISFER is to make full use of neurofeedback paradigm in the context of rehabilitation and psychiatric disorders. The major breakthrough will come from the use of a coupling model associating functional and metabolic information from Magnetic Resonance Imaging (fMRI) to Electro-encephalography (EEG) to "enhance" the neurofeedback protocol. We propose to combine advanced instrumental devices (Hybrid EEG and MRI platforms), with new man-machine interface paradigms (Brain computer interface and serious gaming) and new computational models (source separation, sparse representations and machine learning) to provide novel therapeutic and neuro-rehabilitation paradigms in some of the major neurological and psychiatric disorders of the developmental and the aging brain (stroke, attention-deficit disorder, language disorders, treatmentresistant mood disorders, ...).

Contribution of PANAMA: PANAMA, in close cooperation with the VISAGES team, contributes to a coupling model between EEG and fMRI considered as a joint inverse problem addressed with sparse regularization. By combining both modalities, one expects to achieve a good reconstruction both in time and space. This new imaging technique will then be used for improving neurofeedback paradigms in the context of rehabilitation and psychiatric disorders, which is the final purpose of the HEMISFER project.

9.1.1.2. TEPN

Participant: Rémi Gribonval.

Acronym: TEPN (Toward Energy Proportional Networks)

http://www.tepn.cominlabs.ueb.eu/

Research axis: 3.1

CominLabs partners : IRISA OCIF - Telecom Bretagne; IETR SCN; IETR SCEE; EPI PANAMA Coordinator: Nicolas Montavont, IRISA OCIF - Telecom Bretagne

Description: As in almost all areas of engineering in the past several decades, the design of computer and network systems has been aimed at delivering maximal performance without regarding to the energy efficiency or the percentage of resource utilization. The only places where this tendency was questioned were battery-operated devices (such as laptops and smartphones) for which the users accept limited (but reasonable) performance in exchange for longer use periods. Even though the end users make such decisions on a daily basis by checking their own devices, they have no way of minimizing their energy footprint (or conversely, optimize the network resource usage) in the supporting infrastructure. Thus, the current way of dimensioning and operating the infrastructure supporting the user services, such as cellular networks and data centers, is to dimension for peak usage. The problem with this approach is that usage is rarely at its peak. The overprovisioned systems are also aimed at delivering maximal performance, with energy efficiency being considered as something desired, but non-essential. This project aims at making the network energy consumption proportional to the actual charge of this network (in terms of number of served users, or requested bandwidth). An energy proportional network can be designed by taking intelligent decisions (based on various constraints and metrics) into the network such as switching on and off network components in order to adapt the energy consumption to the user needs. This concept can be summarized under the general term of Green Cognitive Network Approach.

Contribution of PANAMA: PANAMA, in close cooperation with the SCEE team at IETR (thesis of Marwa Chafii), focuses on the design of new waveforms for multi carrier systems with reduced Peak to Average Power Ratio (PAPR).

9.1.2. OSEO-FUI: S-POD: "Assistance à personnes en danger potentiel"

Participants: Frédéric Bimbot, Romain Lebarbenchon, Ewen Camberlein, Jérémy Paret, Vincent Soupé.

Duration: August 2012-December 2015

Research axis: 3.2

Partners: ERYMA, CAPT/FOTON, CASSIDIAN, KAPTALIA, KERLINK, le LOUSTIC and Telecom Bretagne

Coordinator: ERYMA

Description: S-POD gathers research teams and industrial partners to that aim at setting up a framework to process and fuse audio, physiological and contextual data. The goal is to design an embedded autonomous system able to detect situations of potential danger arising in the immediate environment of a person (military, police, CIT, fire, etc.)

Contribution of PANAMA: PANAMA is in charge of R&I activities related to the qualitative and quantitative analysis of information from the acoustic environment (intensity, direction of arrival, nature of noise sounds, properties of voices, etc.) as well as to the exploitation of these analyses. The need for real-time embedded processing induces specific constraints.

9.1.3. OSEO-FUI: voiceHome

Participants: Nancy Bertin, Frédéric Bimbot, Romain Lebarbenchon, Ewen Camberlein.

Duration: 3 years (2015-2017)

Research axis: 3.2

Partners: onMobile, Delta Dore, eSoftThings, Orange, Technicolor, LOUSTIC, Inria Nancy

Coordinator: onMobile

Description: The goal of the project is to design and implement a multi-channel voice interface for smart home and multimedia (set-top-box) appliances.

Contributions of PANAMA are focused on (i) audio activity monitoring and wake-up word detection and (ii) audio source localization and separation. In both cases, the issue of energy frugality is central and strongly constrains the available resources. We expect from this cooperation to make progress towards operational low-resource audio source separation schemes and we intend to investigate compressive sensing for the characterization of audio and voice activity.

9.2. European Initiatives

9.2.1. FP7 & H2020 Projects

9.2.1.1. ERC-StG: PLEASE (Projections, Learning, and Sparsity for Efficient Data Processing)

Participants: Rémi Gribonval, Srdan Kitic, Pierre Machart, Luc Le Magoarou, Nancy Bertin, Nicolas Keriven, Yann Traonmilin, Laurent Albera, Gilles Puy, Thomas Gautrais, Nicolas Bellot.

Duration: January 2012 - December 2016

Research axis: 3.1

Principal investigator: Rémi Gribonval

Program: ERC Starting Grant

Project acronym: PLEASE

Project title: Projections, Learning and Sparsity for Efficient data processing

Abstract: The Please ERC is focused on the extension of the sparse representation paradigm towards that of sparse modeling, with the challenge of establishing, strengthening and clarifying connections between sparse representations and machine learning

Web site: https://team.inria.fr/panama/projects/please/

9.3. International Initiatives

9.3.1. Inria International Partners

9.3.1.1. Informal International Partners

PANAMA has strong recurrent collaborations with the LTS2 lab at EPFL, the Center for Digital Music at Queen Mary University of London, the Institute for Digital Communications at the University of Edimburgh.

9.4. International Research Visitors

9.4.1. Visits of International Scientists

- Pierre Vandergheynst, in July, Professor of Signal and Image Processing, EPFL (Chaire Internationale Inria)
- Gitta Kutyniok, in April, Professor, Technical University of Berlin

10. Dissemination

10.1. Promoting Scientific Activities

Rémi Gribonval is a member of the IEEE Technical Committee on Signal Processing Theory and Methods (2012–2014), and a member of the Awards sub-committee.

Rémi Gribonval is a member of the program committee of the GRETSI.

Rémi Gribonval is a member of the Steering Committee of the SPARS international workshop (chairman until 2013).

Frédéric Bimbot is the Head of the "Digital Signals and Images, Robotics" in IRISA (UMR 6074).

Frédéric Bimbot is a member of the International Advisory Council of ISCA (International Speech Communication Association).

Rémi Gribonval and Frédéric Bimbot are the scientific coordinators of the Science and Music Day (Journée Science et Musique) organized by IRISA.

R. Gribonval was a keynote speaker at LVA/ICA15, and a tutorial speaker at IEEE-SchoolOfICASSP15.

R. Gribonval is guest editor of a special issue of IEEE Journal on Selected Topics in Signal Processing, on Structured Matrices in Signal and Data Processing.

R. Gribonval was vice-president of the jury of the GDR ISIS / GRETSI / Club EAA thesis prize in signal and image processing 2014.

Nancy Bertin is a member of the IEEE Technical Committee on Audio and Acoustic Signal Processing (2013–2015).

Nancy Bertin and Frédéric Bimbot guest edited a special issue of the journal "Traitement du Signal" (Lavoisier).

Laurent Albera is substitute member of the french national board of universities (section 61) (2015-2019).

10.2. Teaching - Supervision - Juries

10.2.1. Teaching

Licence : N. Bertin, "Discovery of selected topics in audio signal processing research", 9 hours, L3, École Supérieure de Réalisation Audiovisuelle (ESRA), France.

Master : N. Bertin, "Audio rendering, coding and source separation", 9 hours, M2, Université Rennes 1, France.

Master : N. Bertin, "Audio indexing and classification", 9 hours, M2, Université Rennes 1, France.

Master : N. Bertin, "Fundamentals of Signal Processing", 24 hours, M1, Ecole Normale Supérieure de Bretagne, Rennes, France.

Master : R. Gribonval, "Signal and image representations", 8 hours, M2, Université Rennes 1, France.

Master: R. Gribonval, coordination of the ARD module "Acquisition et Représensation de Données", M2, Université Rennes 1, France.

Laurent Albera gives lectures in Mathematics and in Signal Processing, and he supervises end of school year projects, mainly at the university of Rennes 1:

Licence: L. Albera, "Mathematics for electronics", 6 hours, L2, Université Rennes 1, France.

Licence: L. Albera, "Mathematics for electronics", 21 hours, L3, Université Rennes 1, France.

Licence: L. Albera, "Mathematics", 53 hours, L3, Ecole Supérieure d'Ingénieurs de Rennes, France

Master: L. Albera, "Cardiac source localization from ECG signals", project supervision (with Ansys), M2, Ecole Supérieure d'Ingénieurs de Rennes, France.

Master : L. Albera, "Blind equalization", 4.5 hours, M2, Université Rennes 1, France.

Master : L. Albera, "Inverse problems", 3 hours, M2, Université Rennes 1, France.

Laurent Albera is responsible of the "Signal Processing" branch of the SISEA (Signal, Images, Embedded Systems and Control) Master 2 of University of Rennes 1.

10.3. Popularization

10.3.1. Journée science et musique

Participants: Nicolas Keriven, Luc Le Magoarou, Stéphanie Lemaile, Frédéric Bimbot, Rémi Gribonval, Gilles Puy, Nancy Bertin, Corentin Guichaoua, Srdan Kitic, Ewen Camberlein, Romain Lebarbenchon, Nathan Souviraà-Labastie.

with contributions and support from: Valérie Gouranton, Laurent Perraudeau, Nathalie Denis, Evelyne Orain, Julie Newton, Agnès Cottais, Cagdas Bilen, and many more.

PANAMA coordinated the organization of a public event called "Journée Science et Musique" (Day of Music and Science). This yearly event organized by the METISS/ PANAMA Team since 2011 aims at sharing with the wide audience the latest innovations and research projects in music. The motivation for hosting this event is to explain and promote the technology behind audio-processing that people face in their daily lives. The event is free to everyone and people have the possibility to attend talks by selected speakers or meet numerous experts that demonstrate current projects in which people can interactively participate. Edition 2015 hosted more than 250 visitors and was the official opening event of the "Festival des Sciences" week in Rennes.

10.3.2. Radio and press

Nancy Bertin and Rémi Gribonval co-authored a popularization article about compressed acoustic holography (with L. Daudet and F. Ollivier). It was published in the journal "Pour la Science" in May 2015 [46].

Nancy Bertin was interviewed for the local press (Rennes Métropole journal) at the occasion of "Journée Science et Musique".

11. Bibliography

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