Activity Report 2017

Team OBELIX

Environment Observation through Complex Imagery

D5 – Digital Signal & Images, Robotics

1 Team composition

Head of the team

Sébastien Lefèvre, Professor, Université Bretagne Sud

Université Bretagne Sud staff

Nicolas Courty, Associate Professor, HDR
Laetitia Chapel, Assistant Professor
Luc Courtrai, Assistant Professor
Chloé Friguet , Assistant Professor
François Merciol, Assistant Professor

Associate/external members

Thomas Corpetti, Senior researcher (DR), CNRS
Romain Dambreville, Researcher, WIPSEA
Yann Le Guyadec, Assistant Professor, Université Bretagne Sud
Romain Tavenard, Assistant Professor, Université Rennes 2

Post-docs

Bharath Bhushan Damodaran, ASTERIX and DeepOT projects
Pierre Gloaguen, SESAME project, since June 2017
Minh-Tan Pham, DELORA project

PhD students

Nicolas Audebert, ONERA grant, since October 2015
Adeline Bailly, RB/ANR grant, since February 2015
Yanwei Cui, RB/CG56 grant, started in Oct. 2013, defended on Jul. 4th, 2017
Roberto Giudici, RB/UBS grant, started in Oct. 2015, withdrawn in Aug. 2017
Florent Guiotte, RB/Tellus grant, since October 2017
Romain Huet, RB/CominLabs grant, started in Oct. 2013, defended on Jun. 19th, 2017
Jamila Mifdal, UBS grant (with LMBA and UIB), since October 2015
Mathieu Laroze, CIFRE Wipsea, since June 2016
Arthur Le Guennec, UR1 grant, since September 2016
Sina Nakhostin, RB/UBS grant, started in Oct. 2013, defended on Dec. 13th, 2017
Ahmed Samy Nassar, OBELIX/ETH Zurich grant, since September 2017
Caglayan Tuna, CNES/CLS grant, since October 2017
Titouan Vayer, UBS grant, since November 2017

Master and DUT students

Thibaud Balem, IUT Vannes, April – July 2017
Dorian Fragni, IUT Vannes, April – June 2017
Nader Georgi, UBS, January – July 2017
Stevan Leber, IUT Vannes, April – June 2017
Alexis Loret, IUT Vannes, April – June 2017
Stiven Morvan, IUT Vannes, April – June 2017
Erwan Vautier, ENSAI Rennes, June – August 2017

2 Overall objectives

2.1 Overview

Observation is one of the key issues in the understanding of environmental systems. A large amount of possibilities, ranging from local probes or networks to hyperspectral remote sensing images, is at the moment available to sense and extract environmental parameters. Among them, aerial or satellite imaging sensors allows for observation at a very large scale. But Earth Observation raises also fundamental challenges. Its impacts are numerous and related to a wide range of application fields, often related to environmental issues: agricultural monitoring and planning for a better exploitation of crops and fields; urban remote sensing for built-up area assessment, urban-natural interaction understanding, pollution monitoring, etc.; analysis of coastal ecosystems through geomorphology studies; land cover mapping and monitoring for identifying the impact of our society on Earth; crisis management and global security aiming to deliver rapid and critical information to rescue operations, e.g., damage assessment, flood delineation, etc. These last applications require fast and even real-time tools for remote sensing.

Unsurprisingly, the number and the complexity of applications based on earth observation are continuously growing. Indeed, our society benefits from the availability of a wide range of earth observation satellites, and several new sensors are launched every year. Within Europe, the Sentinel Copernicus program aims to freely deliver 4 TB daily within the next few years. The dynamics of the remote sensing field leads today to abundant resources of geospatial image data. This advantage has now turned into a serious issue when one has to explore the available data to find some information of interest, and geospatial big data becomes one of the major challenges to be addressed within computer and information sciences. Indeed, how not to be lost in the massive amount of available geospatial data, not far from reaching the Zettabyte scale (ZB)?

Beyond the exceptional data volume to be handled in remote sensing, image intrinsic complexity also brings hard scientific and technological challenges. With the continuous improvement of earth observation satellite sensors, geospatial data are now: multi- or even hyperspectral delivering rich information about observed objects or lands from across the electromagnetic spectrum, beyond the visible light our visual system is used to deal with; daily observations of the same part of Earth which can be revisited by a satellite with ever higher frequencies; at a high or even very-high resolution, allowing to observe from space (from a distance of more than 500km) what occurs on the ground on only 30 centimeter square. This also raises the problem of multiple observations of the same object or part, at various resolutions, and thus with various viewpoints expecting to deliver a globally better understanding of our environment. Moreover, the generalization of very high spatial resolution sensors has a direct influence on the data volume tackled by methods and systems in the field, with an increase of an order of magnitude of 10,000 (one Landsat pixel was representing 30m2 while one WorldView-3 pixel will represent 31cm2). Finally, the complexity also comes from the significant noise, imprecision, and incompleteness that characterized observations provided by remote sensing.

Key Issues. The overall objective of the team is the processing of complex images for environmental purposes. In such a context, available data form a massive amount of multidimensional (multi- or hyperspectral) noisy observations with high spatio-temporal variability and coming from multiple sources. While understanding these data stays very challenging, environmental systems always come with some additional knowledge or models that are worth being exploited to achieve environment observation. Finally, whatever the task involved (e.g., analysis, filtering, classification, clustering, mining, modeling, etc.), specific attention has to be paid to the way results are provided to the end-users, helping them to benefit from their added value.

2.2 Scientific foundations

2.2.1 Processing complex environmental data

Environment observation requires one to perform various data processing tasks: analysis to describe the data with relevant features; filtering and mining to highlight significant data; clustering and classification to map data with predefined or unknown classes of interest; and modeling to understand the underlying phenomena. In this context, processing complex data brings various challenges that will be addressed by the team, both from theoretical and computational points of view. Highly dimensional images, massive datasets, noisy observations, fine temporal and spatial scales, together motivate the design of new dedicated methods that can handle this complexity. The underlying techniques refer to scale-space models (e.g., using hierarchical tree-based image representations) for feature extraction and manifold learning for the theoretical part, and to massive computing using GPUs networks and data intensive systems (based on Hadoop for instance) for the operational level.

Observing data at multiple scales Multiscale modeling of an image enables the access, analysis, processing, understanding and interaction with the image at various levels of details, but also enables one to provide some independence to raw geospatial data, thus introducing a way to deal with the intrinsic complexity of heterogeneous geospatial image repositories. This will allow real-time global land cover monitoring, and foster geospatial description and learning methods to anticipate future challenges faced by our data-intensive society.

Geospatial objects of interest, such as buildings or military targets, manifest themselves most often at various scales within and across the acquired images. Moreover, the clarity of interactions among landscape components (with the purpose of compound object recognition for instance) can also vary greatly with respect to the observation scale. Consequently, image representation schemes capable of accommodating multiple scales are invaluable in the context of geospatial data analysis. Besides, the wide acclaim of the object-based image analysis paradigm has further emphasized the need for multiscale image representation methods [Bla10]. This paradigm relies on a prior segmentation step that aims to gather pixels into regions for further analysis. The team

[Bla10] T. Blaschke, "Object based image analysis for remote sensing", *ISPRS Journal of Photogrammetry and Remote Sensing 65*, 1, 2010, p. 2–10.

has introduced various efficient segmentations algorithms, with a focus on supervised techniques that rely on user knowledge or input.

In particular, given a satellite image at a single resolution, various methods have been designed for constructing its multiscale representation. Wavelets and Gaussian pyramids for example, are popular multiresolution tools in this regard, employed especially with the purpose of image fusion (pan sharpening) and change detection. Unfortunately, they fail to preserve the contours of the image components, and consequently do not lend themselves well for multiscale object-based image analysis. Hierarchical representations form a relevant alternative introduced by the mathematical morphology community. Among the available tree models belonging to this category, partition hierarchies consist of producing segmentation maps of their input at various coarseness levels, with the latter being directly related to the scale under consideration. Inclusion hierarchies rely on the iterative nesting of image components, e.g., from isolated extrema to larger objects. Both models enable efficient representation and direct subsequent extraction of meaningful image regions at arbitrary scales. Hence, multiple tree models relying on these powerful representations have been introduced [SW09], e.g., binary partition trees, or min/max trees. Moreover, certain tree variations can accommodate flexible segmentation strategies according to arbitrary criteria, while additionally preserving the contours of image components [PLCS12]. We explore in the team how to build such hierarchical models from large and multivariate datasets. In order to face the inherent complexity of remote sensing data, we also consider to exploit some prior knowledge when constructing the image model, e.g., in high dimensional spaces.

The description of image content (or feature extraction) is a stage of crucial importance for various geospatial applications, such as content-based retrieval, classification and mapping. Consequently, a plethora of content descriptors have been elaborated in this regard, either at pixel, region or global level, capturing spectral, textural, shape-based, geometric and even localized image properties. Even though content-description approaches have come a long way in the past couple of decades, the challenges, practical requirements and complexity of the data under consideration have increased just as much, if not more. Indeed, content description has to be robust against global and local illumination, rotation, scale variations and geometric deformations. Moreover, with the advances in terms of spatial and spectral resolutions, content descriptors are expected to adapt to their variations, so as to exploit the additional information; for instance by means of descriptors capable of capturing fine spectral image characteristics, or even particular spatial arrangements of predefined objects. Furthermore, the availability of time series has enabled a whole new level of temporal queries that require suitable temporal features. The team aims to elaborate such original and robust features, e.g., with a focus on morphological attributes taking into account some prior knowledge.

Facing the curse of dimensionality Environmental data usually come with high dimensionality, either in the number of samples or in the number of dimensions per

[SW09] P. Salembier, M. Wilkinson, "Connected operators", *IEEE Signal Processing Magazine 6*, 6, 2009, p. 136–157.

[PLCS12] B. Perret, S. Lefèvre, C. Collet, E. Slezak, "Hyperconnections and hierarchical representations for grayscale and multiband image processing", *IEEE Transactions on Image Processing 21*, 1, January 2012, p. 14–27.

sample. A good example is found in Hyperspectral Imaging, where a pixel is a vector of reflectances sampled over different wavelengths, and an image is therefore a data cube usually containing several hundreds of reflectances per pixel. This dimensionality comes with several problems that arise either from a statistical viewpoint (curse of dimensionality) or from computational issues. A good solution is found in dimensionality reduction techniques, which hopefully provide concise representation of the initial information. This reduced information set could be obtained through the embedding of the original data in a lower dimensional but meaningful space. This embedding usually stems from a variety of different energy functions to be optimized, generally associated to the quality of reconstruction of the samples from the embedding space to the original input space. The matrix factorization problem provides a well-grounded framework to a wide class of dimensionality reduction techniques. By decomposing a given data matrix into a product of two matrices (representing respectively the embedding space and the surrogate representation on the data in this space), one can find the expression of several well known transformations by setting constraints on the embedded space or the decomposition. Hence, the Principal Component Analysis is obtained when an orthogonality constraints is set on the vectors of the embedding space. Setting a positivity constraint on both matrices lead to the well known nonnegative matrix factorization. Adding sparsity constraints on the embedding vectors leads to sparse PCA techniques, while imposing it on the reduced coordinates lead to the sparse coding.

We have started in the team to work extensively on the convex formulation of these problems, since it buries strong relations with the underlying physics of the phenomena: the observed data are then assumed to a be mixture of existing, identified, components. As examples, in the case of hyperspectral data, at a given location, and because of the spatial resolution of the captor and scattering effects, the value contained in one pixel is assumed to be a combination of several spectra that describe the reflectance of a "pure" material (e.g., soil, water, asphalt, etc.). Those materials are said to be endmembers. The problem of unmixing [BDPD+12] those data amounts to find which of those endmembers are present in the pixel spectrum, and in which proportion (abundance). This constitutes a difficult ill-posed inverse problem for which no closed-form solutions are available, but where matrix factorization techniques provide appealing solutions (e.g. sparsity constraints or convexity constraints). We also plan to use those kind of technique for the analysis and unmixing of time series representing land covers.

Also, the dimensionality problems can be solved to some extent by subsampling the original dataset, and providing this way a subset of the data which contains most of the relevant information. As a matter of fact, this subsampling problem buries a lot of resemblances with the matrix factorization problem, since they both try to identify low ranks approximations of the original data matrix. In the literature, this sub-sampling problem is also referred to as precise definition or, as coarse graining. Several criteria can be defined to evaluate the quality of this approximation: Minimization of the eigenvector distortion, label propagation, spectrum perturbation, maximization of the data coverage and diversity, etc. Sometimes, these methods make the assumption that the dataset

[BDPD+12] J. M. Bioucas-Dias, A. Plaza, N. Dobigeon, M. Parente, Q. Du, P. Gader, J. Chanussot, "Hyperspectral unmixing overview: Geometrical, statistical, and sparse regression-based approaches", *Selected Topics in Applied Earth Obs. & Remote Sensing, IEEE J. 5*, 2, 2012, p. 354–379.

lives onto a smooth manifold, the structure of which should be preserved through the sub-sampling process. Among others, it is possible to characterize the manifold thanks to the Laplace-Beltrami operator, which is a generalization of the Laplace operator to Riemannian manifolds. In [CL06], the Laplace-Beltrami operator is shown to be fairly well approximated by the Gaussian kernel, exhibiting a strong link between the manifold study and kernel methods in machine learning (with RBF kernels) from which the team has designed a new manifold learning algorithm [CBJ11]. Furthermore, the team is studying the manifold in the input space, or its image in the feature space induced by a kernel, and is further exploring the problem of low rank approximations with dedicated and scalable kernel methods.

Adapting distributions and correcting data shifts Domain adaptation problems occur naturally in many applications of machine learning to real-world datasets [QCSSL09]. In remote sensing image analysis this problem arises frequently, since the acquisition conditions of the images (cloud cover, acquisition angle, seasonal variations) are most often different. As a consequence, even if the images contain the same type of objects, the observed data distribution undergoes a d-dimensional and often nonlinear spectral distortion, i.e. a distortion that is local, class-specific and that impacts differently each region of the electromagnetic spectrum.

One way to solve this problem is to perform an adaptation between the two d-dimensional image domains, in order to achieve a relative compensation of the shift by matching the data clouds to each other. Provided that the data are expressed as graphs and embed a topological structure, this problem can be seen as a graph matching problem and has been tackled as such in hyperspectral remote sensing.

Dealing with time series and dynamic patterns With the growing temporal resolution of remote sensors come new challenges including knowledge extraction from these large temporal datasets. New methods should then be designed so as to better understand dynamics of the observed phenomenons. One possible application is the monitoring of agricultural plots from series of remote sensing images. Here, data are available and their temporal resolution is such that a fine-grained analysis of farming behaviors can be performed.

Time-sensitive metrics (such as Dynamic Time Warping, DTW) have shown great impact on many time series retrieval tasks. We intend to investigate the use of such metrics at the core of machine learning and/or indexing algorithms. This implies to tackle two main (and related) issues.

First, many of these algorithms rely on the assumption that similarity between objects can be measured using distances, or metrics that are distances in some (possibly

[CL06] R. Coifman, S. Lafon, “Diffusion maps”, *Applied and Comput. Harmonic Anal. 21*, 1, 2006, p. 5–30.

[CBJ11] N. Courty, T. Burger, L. Johann, “PerTurbo: a new classification algorithm based on the spectrum perturbations of the Laplace-Beltrami operator”, *in: ECML/PKDD, 1*, p. 359–374, 2011.

[QCSSL09] J. Quiñonero-Candela, M. Sugiyama, A. Schwaighofer, N. D. Lawrence, *Dataset shift in machine learning*, *Neural information processing series*, MIT Press, Cambridge, MA, 2009.

unknown) spaces (this is the case of kernel functions), which is not the case for standard time-sensitive metrics. This has several implications on the use of time-sensitive metrics for machine learning. Some algorithms (*e.g.* k-means) make intensive use of barycenter computations: when using DTW-like metrics, new methods to approximate these as best should be introduced [PKG11]. Other algorithms, in the context of indexing, rely on triangular inequality to prune out the search space at query time. When such inequality does not hold, new pruning methods should be designed so as to perform efficient queries.

Second, most machine learning algorithms make intensive use of distance computations, which can be affordable if the considered distance is fast to compute but becomes a strong limitation when using DTW-like metrics. In order to deal with this issue, fast yet approximate computation of such distances could be used at the core of machine learning algorithms so as to trade accuracy for efficiency.

2.2.2 Incorporating prior knowledge and models

To deal with the intrinsic complexity of images, environment observation can most often benefit from supplementary information (additional measurements, expert knowledge, physical models). Incorporating such information when processing environmental data is thus highly expected. We will address this issue in four different ways: i) data assimilation when dealing with physical models; ii) data fusion and dimensionality reduction when dealing with additional measurements, iii) active learning for interactions with expert knowledge and iv) supervision in the early steps of computer vision (e.g., feature extraction, image segmentation and representation, etc.). The two first points are discussed below whereas the third one is presented in the next section. Let us recall that the last point has been addressed in the previous section.

Coupling data and models In general many physical models exist to describe an environmental system. However, such models are rarely compatible with data analysis tools (e.g., models are non-linear and thus do not fit the classic assumptions in computer vision) and it is therefore of prime importance to design alternative strategies able to accurately mix the recent physical models with variables derived from images. Mixing data and models is commonly known as the data assimilation problem that has largely been studied in the geosciences community. However some specific difficulties due to the intrinsic nature of images (high dimension, 2D/3D projections, indirect observations, etc.) require the design of adapted methodologies.

From a thematic point of view, we will focus on two main applications: the recovery of small-scale velocity fields and the estimation of bio-physical parameters. Although these two aspects seem to be disconnected, they are of prime importance for us since: (i) they require the use of complementary data (low spatial resolution satellite with high temporal rate for wind fields and conversely, high and very high spatial resolution for biophysical parameters with low temporal rate); (ii) associated models are of different nature; we will thus explore a large panel of solutions; and (iii) as longer-term goal, we

[PKG11] F. Petitjean, A. Ketterlin, P. Gançarski, "A global averaging method for dynamic time warping, with applications to clustering", *Pattern Recognition 44*, 3, 2011, p. 678–693.

plan to use complex models of climate/land cover interactions that require the knowledge of both biophysical variables and local winds (as pollutant dispersion or landscape evolution models).

From a methodological point of view, variational data assimilation and stochastic filtering techniques will be explored. Indeed, promising results have been obtained very recently through approaches relying on optimal control theory and data assimilation. The techniques proposed melt an imperfect modeling (based on Partial Differential Equations) of the physical process and an observation operator, leading to adequate optimal tools for consistent combination of model and observations. In this context the variational approach (3D-4D var) is a popular methodology. For turbulent 2D flows, curve and front tracking or data reconstruction from images, this enabled the recovering of the whole scale range of the flow. However as already mentioned, it has been observed that errors still remain on the fine scale structures. Yet, they are of prime importance in many applications related to climate and land-cover interactions as urban pollution understanding.To deal with fine scales, we will rely on our first works that consist in performing a multi-scale estimation by exploiting the framework of data assimilation where the usual temporal variable is now an artificial time between scales and the models are based on downscaling laws issued from fluid mechanics. We will rely on various observation operators: image-based ones and direct observations (issued from local sensors at lower altitudes) in order to estimate, in a single scheme, the velocities at various layers of the atmosphere by keeping the physical interactions between these layers. To that end, a large variety of physical models of scale interactions will be explored. These models are mainly developed in the Turbulence Laboratory of Tsinghua University (Beijing, China) with which we have many links and projects. The design of adapted image-based observation operators (link between the image luminance and the fine scale velocities) and the adaptation of existing physical models to this specific problem will be the key axes of researches.

When dealing with land cover studies, main parameters to be extract from remotely sensed data are: kind of land cover (built areas, water, roads or vegetation), surface roughness, temperature, moisture and the LAI (Leaf Area Index, related to the vegetation). In practice all parameters of interest can already be estimated from images. Let us however mention that in specific environments (urban, highly intensive agricultural landscapes), the estimation of the temperature is delicate since many interactions between land cover and temperature occur. We will thus build upon some previous work from OSUR [FDQ12] to design precise temperature estimation tools in urban environments. The idea is to adapt the existing models of temperature (at regional scales) to the scale of a city by extracting correlations/statistical relations between land cover and temperature. These relations will be computed from sparse representations and manifold learning techniques discussed in previous section. The specific case of bio-physical parameter and in particular LAI estimation will also be managed through stochastic filtering techniques. The underlying physical process of annual growth of leaves is indeed known and this information is at the moment not taken into account in existing and operational estimation tools. It may therefore be of high interest to take this knowledge

[FDQ12] X. Foissard, V. Dubreuil, H. Quenol, "Spatialization of urban heat island by multi regression in Rennes, France", *in: 8th International Conference on Urban Climate*, *2*, Dublin, Ireland, 2012.

into consideration. It has indeed two advantages: i) reduction of the noise and interpolation of missing data associated to the low temporal observations and ii) extraction of some hidden parameters related to the calibration of the dynamic models. We have been involved in this direction for the recovery of bio-physical parameters from medium resolution images in collaboration with the CPLANT team of CASIA (Institute of Automation of Chinese Academy of Sciences) which develops since more than 30 year a well known plant growth model (named GreenLab). Within the OBELIX team, we plan extend our first works and move from medium resolution to very high resolution data. As the GreenLab model requires many calibration parameters and is highly non linear, we will rely both on reduction techniques (to learn some parameters on known data sets) and particle-smoothing approaches which are more adapted to the manipulation of complex models than the variational data assimilation (in particular they do not require adjoint models which are tricky to design with GreenLab).

Combining various sources of information Since complementary observations are available for analyzing land cover parameters or winds (a wide range of remote sensing data, a set of on site measurements, hemispherical photographs, surveys), a specific care should be done regarding the combination of these data: even if mixing various sources can generally improve the quality of the estimation, an improper handling of this wealth of information is sometimes likely to introduce more noise and uncertainty in the measurement than expected precision. Combining this information is a crucial step since extracting values with a minimum of noise is the key point for analyzing and understanding the land covers. An accurate management and homogenization of this mass of information is then essential in order to extract usable time series. In particular, reducing the uncertainty is the fundamental issue when observations have variable degrees of confidence. Here we will explore the theory of evidence that is particularly suited to decision making by management of uncertainty [Sha76]. We recently explored this aspect to combine observations in order to detect edges in satellite images, to detect changes in remote sensing data from past and present or to evaluate the influence of climatic parameters on the land. Recently, several theoretical extensions have been proposed in order to properly handle sources of data potentially paradoxical, subjective or symbolic [DS06] or to apprehend correlated sources [Den99]. We will explore such solutions that are perfectly suited to the variety of data we have to deal with.

2.2.3 Putting the user in the loop

Since most of the results of the methodological developments of the team will be aimed towards nonspecialists of computer science (computer vision and image processing, machine learning and data mining), a particular focus will be given to their understanding by the end-user. The objectives are both to facilitate their interactions with the tools, and provide easy ways to understand the results of the different algorithms. We refer to

[Sha76] G. Shafer, *Mathematical Theory of Evidence*, Princeton University Press, 1976.

[DS06] J. Dezert, F. Smarandache, "Introduction to the Fusion of Quantitative and Qualitative Beliefs", *Information and Security 20*, 2006, p. 9–49.

[Den99] T. Denoeux, "Reasoning with imprecise belief structures", *Int. J. Approx. Reasoning 20*, 1, 1999, p. 79–111.

the first category as "active processing", where the user is supposed to interact with the algorithm to achieve a better result, and to the second one as "visual analytics", since the visualization of the algorithm results is meant to provide a thorough understanding of the observed phenomenon.

Active processing Analysis and understanding of EO images is usually performed in a supervised mode, where the expert is able to provide a representative learning dataset. The latter usually contains a sufficient information about the underlying distributions, which is usually not true, mostly because the labelling activity is time consuming (and also prone to errors), and also because only few criteria can be designed to assess the completeness of descriptions. As a matter of fact, increasing the learning set size can be efficiently done if the learning algorithm is endowed with auto-analysis properties, and is capable of determining which is the best information to add to the system (which samples should be labelled to gain accuracy in the class models, or in the boundaries between the classes). It then ask the user to label this data (or a subset of the data). Yet, this problem of active learning has been well studied in the previous decades, and has also been completed by recent advances in the context of semi-supervised learning, which assumes that also the unlabelled samples can be used for learning class models or driving feature extraction. We propose nethertheless to work on this type of active learning strategies, either by designing new strategies to determine the missing pieces of the learning (such as the one developed in the Perturbo framework or by integrating prior knowledges from physical models or simulation methods in the active strategy. Here, the learning set is enhanced by samples that are not collected from real data, but automatically produced by a simulation model. This kind of bootstrapping by synthetic data has recently been shown to work successfully in the context of crowd video analysis, and we foresee to extend these concepts to environmental data.

Following the objectives of the team to develop supervised feature extraction and supervised image representation and segmentation, we also consider involving the expert in the earlier steps of computer vision through the active paradigm. Indeed, the team will build upon its expertise on efficient algorithms for image representation and segmentation to propose interactive segmentation and analysis schemes that will let the user to explore its datasets in real-time. Image representations and segmentations will be produced in real-time by tacking into account user feedback, leading to a specific view of the data that fits user needs.

Visual Analytics The multimodal observation of the environment through a variety of sensors, as well as simulation models running at fine scales, contribute to produce a large amount of information, which complexity cannot be handled directly by the user. For this information to be processed directly by a human operator, new paradigms of representations are to be explored. Those paradigms usually involve the visual system, which demonstrates in our day to day life capacities which computer scientists fail to reproduce with computers. Turning an information in a some visual clues or easy-to-apprehend chart is in itself a challenging task. Environmental data, that are in essence spatialized and temporal, can however be easily mapped on animated geocentric earth representations. It remains nonetheless that complex data will lead complex representations, that require one to pre-analyze the data before its visualization, either for computational issues, or either to extract the meaningful information inside.

The team intends to first specialize some methodologies to achieve this goal (e.g., explain some unobserved data by a combination of known data, as can be done with matrix factorization techniques), before considering visualization methods. This last point belongs to the category of visual analytics and can be considered as a crucial step to help decision makers exploit rapidly scientific advances. those aspects constitute some middle-term objectives for the development of the team. To ensure dissemination among the scientific communities, the team aims to follow open-source initiatives and to deliver a series of tools dedicated to the end-user appropriation of results.

3 Scientific achievements

3.1 Hierarchical image analysis

Participants: Sébastien Lefèvre, François Merciol, Laetitia Chapel, Thomas Corpetti, Minh Tan Pham, Bharath Bhushan Damodaran, Yanwei Cui, Caglayan Tuna, Florent Guiotte, Thibaud Balem.

Hierarchical representations provide a powerful way to model, analyze and process images beyond the simple grayscale ones. In particular, we have shown that such hierarchies could be extracted not only from raw data but also from derived channels such as NDVI (normalized difference vegetation index) [6]. Angular data such as motion fields, textures, or color hues, were addressed with the standard morphological toolbox [13], opening the possibility for further modeling with morphological hierarchies. Through the Ph.D. of Caglayan Tuna and Florent Guiotte both initiated in 2017, we will explore how these hierarchies can be applied to satellite image time series and LiDAR point clouds, respectively.

We have also focused on attribute profile, a well-known multiscale feature in remote sensing, built from an inclusion or level-set tree. First, we adapted this concept to the case of partitioning trees (or multiscale segmentations), together with Erchan Aptoula and Mauro Dalla Mura [19]. Second, we extended this profile to take into account local information at each scale, leading to the local feature attribute profile (LFAP), together with Erchan Aptoula [27].

The tree construction step was still receiving some attention, and further algorithmic improvements were made to design a processing chain able to perform large-scale mapping very efficiently [25, 22]. It is used for mapping small woody features at the Pan-European scale with the SIRS SME.

Finally, the doctoral study conducted by Yanwei Cui on kernels for trees was completed, and his results were improved through the use of Random Fourier Features, leading to a consolidated journal publication [4].

3.2 Deep Learning for Remote Sensing

Participants: Sébastien Lefèvre, Nicolas Audebert, Ahmed Samy Nassar.

Our work in semantic segmentation, initiated in 2016 through the Ph.D. of Nicolas Audebert jointly with ONERA, was consolidated and extended in several directions. The use of semantic segmentation as a preprocessing for object detection led to an approach called segment-before-detect [1]. Fusion of multiple modalities in the context of urban remote sensing was addressed in [16, 14, 18]. Even further, we have suggested to rely on some available ancillary data such as OpenStreetMap rasterized images (fed as inputs to the network) to support the training process [17, 15].

We have also tackled the problem of multimodal change detection with a pure deep learning-based approach through the M.Sc. thesis of Ahmed Samy Nassar. Together with other attempts made by colleagues from Switzerland (University of Zurich and ETH Zurich), we have offered a large insight on the potential of deep learning using multiple modalities from street level to satellite imagery, leading to a paper published in Proceedings of the IEEE [10]. The collaboration with Jan Dirk Wegner from ETH Zurich will continue through the joint supervision of the PhD of Ahmed Samy Nassar.

3.3 Optimal Transport for machine learning and remote sensing

Participants: Nicolas Courty, Jamila Mifdal.

Following our works on optimal transport for domain adaptation initiated in 2014, we developed an activity centered around the theme of optimal transport for machine learning.

Domain adaptation. Domain adaptation from one data space (or domain) to another is one of the most challenging tasks of modern data analytics. If the adaptation is done correctly, models built on a specific data space become more robust when confronted to data depicting the same semantic concepts (the classes), but observed by another observation system with its own specificities. Among the many strategies proposed to adapt a domain to another, finding a common representation has shown excellent properties: by finding a common representation for both domains, a single classifier can be effective in both and use labelled samples from the source domain to predict the unlabelled samples of the target domain. In this work, we propose a regularized unsupervised optimal transportation model to perform the alignment of the representations in the source and target domains. We learn a transportation plan matching both PDFs, which constrains labelled samples in the source domain to remain close during transport. This way, we exploit at the same time the few labeled information in the source and the unlabelled distributions observed in both domains. This work was done in collaboration with Devis Tuia, Rémi Flamary (Observatoire de la côte d'Azur, Nice Univeristy), Alain Rakotomamonjy (University of Rouen, LITIS) and Amaury Habrard (University Jean Monnet, Saint Etienne) and has led to one publication in NIPS [20] and one IEEE TPAMI [3].

Hyperspectral and multispectral image fusion based on optimal transport. In this work we tackle the problem of the fusion of hyperspectral (HS) and multispectral (MS) satellite images. The aim of the fusion process is to merge the spectral quality of the HS images with the better spatial resolution of the MS images. The final result is an image having both high spectral and spatial resolution. In order to perform the fusion task, we suggest an approach based on optimal transport theory that highlights the idea of energy transfer from the starting images HS and MS to the resulting final image. In this sense, the map transport can be thought as the transfer of characteristics of one image to another. This work is a part of Jamila Mifdal PhD, published at IGARSS [26].

3.4 Dimensionality reduction and feature selection for hyperspectral data

Participants: Bharath Bushan Damodoran, Nicolas Courty, Sébastien Lefèvre, Romain Tavenard.

Hyperspectral data are generally high dimensional and large scale (several tens of thousands of spectra per image). In the context of Bharath Damodoran post-doc, we developed strategies to cope with these two problems: one based on random Fourier Features for nonlinear component analysis, and one for feature selection in spectral bands for classification.

Randomized Nonlinear Component Analysis for Dimensionality Reduction of Hyperspectral Images. Kernel based feature extraction method overcomes the curse of dimensionality and captures the non-linearities present in the data. However, these methods are not scal-able with large number of pixels found with hyperspectral images. Thus, a small subset of pixels are randomly selected to make the solution of kernel based methods tractable. In this paper, we propose scalable nonlinear component analysis for dimensionality reduction of hyperspectral images. The proposed method relies on the randomized feature maps to capture the non-linearities between the variables in the hyperspectral data. Experiments conducted with different hyperspectral datasets show that our proposed method has provided better quality components and outperformed the state-of-the-art in terms of classification performance. This work was published at IGARSS 2017 [21]

Sparse Hilbert Schmidt Independence Criterion and Surrogate-Kernel-Based Feature Selection for Hyperspectral Image Classification . Designing an effective criterion to select a subset of features is a challenging problem for hyperspectral image classification. In this paper, we develop a feature selection method to select a subset of class discriminant features for hyperspectral image classification. First, we propose a new class separability measure based on the surrogate kernel and Hilbert Schmidt independence criterion in the reproducing kernel Hilbert space. Second, we employ the proposed class separability measure as an objective function and we model the feature selection problem as a continuous optimization problem using LASSO optimization framework. The combination of the class separability measure and the LASSO model allows selecting the subset of features that increases the class separability information and also avoids a computationally intensive subset search strategy. Experiments conducted with three hyperspectral data sets and different experimental settings show that our proposed method increases the classification accuracy and outperforms the state-of-the-art methods. This work was published in a journal paper IEEE TGRS [5].

3.5 Coupling data and models

Participants: Thomas Corpetti.

Mapping temperatures at fine scales from satellite images.

General Circulation Models (GCM) of temperatures can not take into account the local variability due to their low spatial resolution. For fine scale temperature estimation, a classic option is to create model based on Multiple Linear Regression (MLR) using temperature as dependant variable and local parameters (local sensors, slope, topology, ...) as predictor variables. Though efficient, the non-linearity assumption is a strong constraint that limits performances of spatial models at the vineyard scale. We have worked on non linear mappings driven by dynamical models for local temperatures estimation in agricultural parcels [8].

3.6 Change detection and time series analysis

Participants: Adeline Bailly, Laetitia Chapel, Thomas Corpetti, Romain Tavenard, Zheng Zhang.

Time series analysis From a thematic point of view, the analysis of crops and the way they are managed is a very hot point. Therefore, High Spatial Resolution (HSR) remote sensing time series are of prime importance to monitor those systems. However, because of the complexity of the resulting time series, the identification of various practices using conventional tools is no easy task. We have studied the use of match kernels [29], as well as a novel alignment-based metric [12] for time series classification. Another body of work related to alignment-based distances considers learning to mimic such metrics in a Euclidean embedding [23]. We also have identified changes in urban environments and lastly [9], we have considered the domain adaptation framework in the specific case of time series data [2].

3.7 Active learning to assist annotation of aerial images in environmental surveys

Participants: Romain Dambreville, Chloé Friguet, Mathieu Laroze, Sébastien Lefèvre.

Remote sensing technologies greatly ease environmental assessment using aerial images. Such data are most often analyzed by a manual operator, leading to costly and non scalable solutions. In the fields of both machine learning and image processing, many algorithms have been developed to fasten and automate this complex task. Their main common assumption is the need to have prior ground truth available. However, for field experts or engineers, manually labeling the objects requires a time-consuming and tedious process. Restating the labeling issue as a binary classification one, we propose a method to assist the costly annotation task by introducing an active learning process, considering a query-by-group strategy. Assuming that a comprehensive context may be required to assist the annotator with the labeling task of a single instance, the labels of all the instances of an image are indeed queried. A score based on instances distribution is defined to rank the images for annotation and an appropriate retraining step is derived to simultaneously reduce the interaction cost and improve the classifier performances at each iteration.

A first numerical study with promising results regarding the classification rate along with the chosen re-training strategy and the number of interactions with the user has been presented at Statlearn'17 [31].

4 Software development

4.1 Software development

In compliance with ACM requirements, most of our research code is being made available through `http://gitlab.inria.fr/obelix` for reproducibility purposes.

4.1.1 Triskele

Participants: François Merciol.

`TRISKELE` stands for Tree Representations of Images for Scalable Knowledge Extraction and Learning for Earth observation. Triskele is an open source C++ library that provides several algorithms for building hierarchical representation of remote sensing images. (CeCILL-B licence) Source Code (IRISA): `https://gitlab.inria.fr/obelix/triskele/`

4.1.2 Broceliande

Participants: François Merciol.

`Broceliande` is a software for classification of remote sensing images. It uses TRISKELE and Random Forests. (CeCILL-B licence). Source Code (IRISA): `https://gitlab.inria.fr/obelix/broceliande/`

4.1.3 tslearn

Participants: Romain Tavenard.

tslearn is a general-purpose Python machine learning library for time series that offers tools for pre-processing and feature extraction as well as dedicated models for clustering, classification and regression

Website and documentation: `https://tslearn.readthedocs.io` (BSD-2-Clause license)

4.1.4 POT

Participants: Nicolas Courty, Laetitia Chapel, Romain Tavenard.

`POT` is an open source Python library that provides several solvers for optimization problems related to Optimal Transport for signal, image processing and machine learning. It has more than 110k downloads and 640 stars on github.

Website and documentation: `https://PythonOT.github.io/`

Source Code (MIT): `https://github.com/PythonOT/POT`

5 Contracts and collaborations

5.1 International Initiatives

5.1.1 PHC Cai YuanPei – French Ministry of Foreign Affairs

Participants: Thomas Corpetti.

- Project type: PHC
- Dates: 2017–2019
- PI institution: CNRS
- Other partners: Chinese Academy of Sciences, Aerospace Institute Research Center
- Principal investigator: Thomas Corpetti

In a context of climate change, the monitoring of local climate evolution becomes crucial, especially for two main reasons:

- ensure quality of life of humans;
- ensure a sustainable agriculture.

As for the first point, prospective scenario expect that in 2050, 70% of the world population will live in cities (Unesco report, 2015). Ensuring a reliable quality of life in urban environments is then of prime importance. It is today admitted that vegetation can be an answer (it absorbs CO_2, reduces heat, ...). However, today we only have a sparse information of the vegetation inside cities (issued from public) but the amount of green areas issued from individuals is unknown. As for the second point, because of both the modifications in agricultural practices (intensive, increase in fertilization, ...) and the climate change (increasing temperature inside parcels), the evolution of resources and potential of agriculture is a problem that has to be monitored. In both situations (urban and agriculture), it is then of prime interest to monitor, understand and model the interactions between vegetation and local climate at fine scales. Such links are today not well understood at the fine scales we are interested in. This is the goal of this project. Applications concern the cities of Rennes (France), Beijing (China) and a local agricultural parcel near to Yinchuan (China, Ningxia province).

5.1.2 OBIATS - PHC Pamoja

Participants: Sébastien Lefèvre, Romain Dambreville, Mathieu Laroze.

- Project type: PHC Pamoja
- Dates: 2016–2017

- PI institution: UBS
- Other partners: TU Kenya (Kenya)
- Principal investigator: Sébastien Lefèvre

The research aims to utilize the latest development of satellite based remote sensing for acquisition of timely information acquisition of spatio-temporal monitoring on tree species cover crowns within Kenya National Parks. Major application areas are as follows: 1) Development of object based image analysis algorithm for segmentation and pattern recognition of tree species crowns (specifically acacia xanthophloea spp) on remote sensing data sets. 2) Monitoring and characterization of condition and growth of tree species crown, using pixel and over-pixel based spectro- temporal analysis of Remote Sensing data. 3) Integration of step 1 & 2 to develop an integrated Remote Sensing and Geographical Information System methodology for monitoring, mapping and analysis of tree species crown cover within Kenya National Parks. Such an initiative will be an important contribution towards natural resource management. 4) Application of raster fusion techniques on data sets of different resolutions, in order to achieve finer information details of high accuracy for surface features. More precisely, we focus on combining satellite image times series brought by the EU Copernicus Program, namely Sentinel-1 (SAR) and Sentinel-2 (optical), with single-date VHR (either aerial or satellite) imagery.

5.2 National Initiatives

5.2.1 SESAME - ASTRID 2017-2020

Participants: Romain Tavenard (WP leader), Laetitia Chapel, Chloé Friguet, Sébastien Lefèvre, François Merciol.

- Project type: ANR ASTRID
- Dates: 2017–2020
- PI institution: IMT Atlantique (Brest)
- Other partners: IRISA-Myriad (Rennes), CLS (Brest)
- Principal investigator: Prof. Ronan Fablet, IMT Atlantique, Signal & Comm. dept, Lab-STICC TOMS research team
- web: http://recherche.imt-atlantique.fr/sesame

The surveillance of the maritime traffic is a major issue for defense contexts (e.g., surveillance of specific zones, borders,...) as well as security and monitoring contexts (e.g., monitoring of the maritime traffic, of fisheries activities). Spaceborn technologies, especially satellite ship tracking from AIS messages (Automatic Identification System) and high-resolution imaging of sea surface, open new avenues to address such monitoring and surveillance objectives. SESAME initiative aims at developing new big-data-oriented approaches to deliver novel solutions for the management, analysis and visualization of multi-source satellite data streams. It involves four main scientific and technical tasks: Hardware and software platforms for the management, processing and visualization of multi-source satellite data streams for maritime traffic surveillance (Task 1), Analysis, modeling and detection of marine vessel behaviours from AIS data streams (Task 2), AIS-Sentinel data synergies for maritime traffic surveillance (Task 3), Visualization and mining of large-scale augmented marine vessel tracking databases (Task 4). A fifth task embeds the implementation of the proposed solutions for dual case-studies representative of the scientific and technical objectives targeted by the project. A first scientific contribution has been presented at BIDS'17 conference [30].

5.2.2 OATMIL - ANR PRC 2017-2021

Participants: Nicolas Courty (project leader), Laetitia Chapel, Romain Tavenard.

- Project type: ANR OATMIL
- Dates: 2017–2021
- PI institution: UBS
- Other partners: INRIA-Panama (Rennes), LITIS (Rouen), Lagrange (Nice)
- Principal investigator: Nicolas Courty
- web: http://people.irisa.fr/Nicolas.Courty/OATMIL/

OATMIL is a research project that challenges some current thinkings in several topics of Machine Learning (ML). It introduces some paradigm shifts for problems related to machine learning with probability distributions. These shifts and the resulting innovative methodologies are achieved by bridging the gap between machine learning and the theory of optimal transport and the geometrical tools it offers and by rethinking the above ML problems from the optimal transport perspective. The new methodologies will be implemented as a toolbox that will be made available for the research community and potential industrial partners. The contributions of the project will be in 1) the design of new methods and algorithms for fundamental ML problems (e.g. domain adaptation) with optimal transport and 2) the definition of new algorithms for computing optimal transport and its variants on large scale collections of data.

5.2.3 ASTERIX - ANR JCJC 2013-2017

Participants: Sébastien Lefèvre(project leader), Nicolas Courty, Laetitia Chapel, Romain Tavenard, Thomas Corpetti, Bharath Bhushan Damodaran.

- Project type: ANR ASTERIX

- Dates: 2013–2017
- PI institution: UBS
- Other partners: OSUR (Rennes), LIVE (Strasbourg), IPGS (Strasbourg), DYNAFOR (Toulouse)
- Principal investigator: Sébastien Lefèvre
- web: http://www-obelix.irisa.fr/asterix/

Following the growth of multisource data with high spatial, spectral, and temporal resolutions, the problem of complex image information mining in remote sensing of environment becomes a great challenge, with many potential applications raising. However, there is no or only a few methodological frameworks for dealing with data with multiple spatial and temporal scales: recognition methods are most often straight applications of standard classification and modelisation methods. Besides, dealing with spatial and temporal neighborhood, with various kinds of data, is expected to improve significantly resulting performances.

The goal of the ASTERIX project (Spatio-Temporal Analysis by Recognition within Complex Images for Remote Sensing of Environment) and its originality is to bring new methods, algorithms, softwares in the field of image analysis and machine learning in order to support recognition within complex image, by explicitly dealing with the specificity of remote sensing complex images. In this context, main challenges are related to high dimensionality, heterogeneity, volume and spatio-temporal behaviour of images.

Besides methodological achievements supporting the development of the state-of-the-art in image processing and machine learning in the context of recognition within complex images, expected results from the ASTERIX project consist in a set of concrete solutions to crucial problems in remote sensing of environment, and especially in two environment: coastal and montains. More precisely, applications considered are related to the dynamic of environmental objects which help to understand coastal evolution, the dynamic of ash tree colonization in an agricultural mountain landscape, and the dynamic of geological process.

5.2.4 DELORA - Pôle I&R AAP PME 2016-2018

Participants: Sébastien Lefèvre, Minh-Tan Pham (Post-doc).

- Project type: Pôle Images & Réseaux, AAP PME
- Dates: 2016–2018
- PI institution: Tellus (Bruz)
- Other partners: Artefacto (Betton)
- Principal investigator: Geoffroy Etaix (Tellus)

To meet the new requirements of major accounts such as ERDF, GRDF, Suez Environnment, La Lyonnaise des Eaux, ... who would like to perform a precise geolocation and diagnosis of their networks, TELLUS Environment wants to propose with its partners Artefacto and IRISA (OBELIX) a new product ranging from network diagnosis to operational re-geolocation by augmented reality of networks and their defects for the operators of these customers. The aim of the DELORA project is to propose a packaged product including new sensors, 3D decision support software, new multi-source data processing and augmented reality hardware.

5.2.5 Littoralg - PPI UBS 2013-2017

Participants: Sébastien Lefèvre, Luc Courtrai, Roberto Giudici.

- Project type: PPI UBS
- Dates: 2014–2017
- PI institution: LBCM and GMGL labs (UBS)
- Other partners: Geoarchitecture, IREA, CRPCC (all at UBS)
- Principal investigator: Nathalie Bourgougnon (LBCM) and Mouncef Sedrati (GMGL)

LittorAgl is a multi-disciplinary project inside the South Brittany University. The main goal of the project is to monitor and value the brown seaweeds grounded on the departmental beaches. In this context, the OBELIX team task is to monitor brown seaweeds on these beaches by satellite, aerial, or fixed images. Our work consists of the neural network detection and estimation of the brown seaweeds volume on images such as those produced by a UAV. Furthermore, for the reconstruction of images' mosaic, we propose new methods based on the common objects present on those different images. Finally, we propose an evaluation tool for mosaicing algorithms.

5.3 Bilateral industry grants

- Wipsea, Rennes, through a scientific collaboration with Romain Dambreville (research engineer) and a CIFRE Ph.D. (Mathieu Laroze)
- CLS, Plouzané, through a Ph.D. (Caglayan Tuna) co-funded with CNES
- Tellus, Bruz, through a Ph.D. (Florent Guiotte) co-funded with Région Bretagne
- SIRS, Lille, through a scientific collaboration on large-scale mapping with hierarchical image representations ([22])

5.4 Collaborations

National collaborations

- Agrocampus Ouest and IRMAR, Rennes, through a scientific collaboration with Mathieu EMILY (MCF-HDR Statistics) [7]
- Rennes 1 University / IRISA (team LINKMEDIA) through a Ph.D. co-supervision with Ewa KIJAK (MCF) [31]
- DTIS team from ONERA, through a collaboration (PhD cosupervision of Nicolas Audebert [18, 15, 14, 1, 17, 16]) with Bertrand Le Saux (CR ONERA)
- Grenoble INP, GIPSA, through a collaboration with Mauro Dalla (MCF Grenoble INP) Mura [19]
- Geosciences Rennes, through a collaboration (PhD cosupervision of Arthur Le Guennec) with Dimitri Lague (DR CNRS)
- CNES, through the scientific supervision of Antoine Masse (CNES postdoc) on image denoising [24]
- LITIS (Rouen), Observatoire de la Côte d'Azur (Nice), UJM (Saint-Etienne), in the context of the OATMIL ANR (e.g. [20])

International collaborations

- The visit of Adeline Bailly to Gustau Camps-Valls (Universitat de Valencia, Spain) has lead to the publication of a journal article [2]
- Gebze Technical University, Kocaeli, Turkey: Erchan Aptoula (Associate Professor) is collaborating with the team on several topics, mainly related to image retrieval/classification with morphological hierarchies [13, 19, 27]
- University of Aalborg through a collaboration on topographic mapping (joint paper [6]) with Joachim Höhle (Emeritus Prof.)
- ETH Zurich through a Ph.D. co-supervision with Jan Dirk Wegner (Ass. Prof.) and a joint paper written with Devis Tuia from University of Zurich [10]
- Université des Iles Baléares (UIB), Espagne, with Bartomeu Coll (full Professor). We are co-supervising the PhD of Jamila Mifdal on image fusion [26].

6 Dissemination

6.1 Promoting scientific activities

6.1.1 Scientific Events Organisation

Member of the Organizing Committees

- Chloé Friguet : Statlearn'17 (Lyon) : challenging problems in statistical learning

6.1.2 Scientific Events Selection

Member of Conference Program Committees

- Chloé Friguet: Statlearn'17 (Lyon) : challenging problems in statistical learning
- Sébastien Lefèvre: VISAPP 2017 (Porto), JURSE 2017 (Dubai), ISMM 2017 (Fontainebleau), IGARSS 2017 (Fort Worth), BiDS 2017 (Toulouse), CBMI 2017 (Firenze), ICIP 2017 (Beijing), EGC 2017 (Grenoble)
- Laetitia Chapel: IGARSS, ICLR, NIPS, AISTAT, ICML
- Romain Tavenard: AISTAT
- Nicolas Courty: AAAI, CVPR Earthvision workshop, IJCAI (Senior reviewer), NIPS, Orasis

Reviewer

- Chloé Friguet : IGARSS
- Sébastien Lefèvre: IGARSS

6.1.3 Journal

Member of the Editorial Boards

- Chloé Friguet : Associate Editor of *Statistique et Société* (Société Francaise de Statistique) - since May 2017
- Sébastien Lefèvre: Editorial Board Member of Remote Sensing, MDPI; Guest editor of a special issue "Advances in Object-Based Image Analysis – Linking with Computer Vision and Machine Learning" in Remote Sensing, MDPI

Reviewer - Reviewing Activities

- Chloé Friguet: Transactions on Computational Biology and Bioinformatics; IEEE Transactions on Geoscience and Remote Sensing; Statistique et Société
- Romain Tavenard: Springer Data Mining and Knowledge Discovery
- Sébastien Lefèvre: ACM Computing Review, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Proceedings of the IEEE, IEEE Transactions on Geoscience and Remote Sensing, IEEE Geoscience and Remote Sensing Magazine, MDPI Journal of Imaging, PLOS One
- Nicolas Courty: IEEE Transactions on Geoscience and Remote Sensing, Remote Sensing, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing
- François Merciol : MDPI Sensors

6.1.4 Invited Talks

- Sébastien Lefèvre: New Trends in Image Analysis and Machine Learning for Remote Sensing – ESA – Frascati, Italy
- Sébastien Lefèvre: ONERA; LISTIC / Université de Savoie Mont Blanc
- Nicolas Courty: invited talk at PGMO Days (EDF/Saclay) : 'Joint distribution Optimal Transport for domain'
- Nicolas Courty: Introduction course on 'Optimal transport and Machine learning' during the 'Mathematical coffees' (SMAI/Huawei, Paris)
- Nicolas Courty: Invited talk at Rotchester University (RIT) : 'Domain adaptation and optimal transport'

6.1.5 Leadership within the Scientific Community

6.1.6 Scientific Expertise

- Sébastien Lefèvre: Expert for the French Ministry of Higher Education and Research (CIR/JEI), the Belgium National Research Agency (FWO)
- Nicolas Courty: Expert reviewer for ANR

6.1.7 Research Administration

- Sébastien Lefèvre: Head of OBELIX group; Deputy-head of the doctoral school SICMA (head for UBS); Member of the Scientific Council of the Natural Regional Park of the Gulf of Morbihan; Member of the Scientific Council of the Scientific Interest Group BreTel (Remote Sensing in Brittany)

6.2 Teaching, supervision

6.2.1 Teaching

For reseachers, all activities are given. For professors and assistant professors, only courses at the M. Sc. level are listed.

- Chloé Friguet
  - Biostatistique, 21h, M1 Biomolécules, Micro-organismes et Bioprocédés, Univ. Bretagne Sud, Lorient, France
- Romain Tavenard
  - programming, data mining, databases and deep learning, Univ. Rennes 2
- Luc Courtrai
  - concurrent programming, Master 1, Univ. Bretagne Sud, Vannes France
- Nicolas Courty
  - programming, data mining, databases, multimedia coding, machine learning, Master in Computer science, Univ. Bretagne Sud, Vannes France

6.2.2 Supervision

- PhD in progress:
  - Nicolas Audebert, Machine Learning for Classification of Big Remote Sensing Data, 2015-2018, Sébastien Lefèvre, Bertrand Le Saux (ONERA)
  - Adeline Bailly, Classification de séries temporelles et applications à la télédetection, 2015-2018, Romain Tavenard, Laetitia Chapel
  - Sina Nakhostin, Contributions to Unmixing strategies of Hyperspectral data, Nicolas Courty, Thomas Corpetti
  - Florent Guiotte, Morphological characterization of full waveform airborne LiDAR data, 2017-2020, Thomas Corpetti, Sébastien Lefèvre
  - Mathieu Laroze, Active Learning for Object Detection in Aerial Images with Application to Environmental Science, 2016-2019, Romain Dambreville, Chloé Friguet, Sébastien Lefèvre, Ewa Kijak (Univ. Rennes 1)
  - Arthur Le Guennec, Classification of massive 3D topo-bathymetric airborne lidar data in fluvial environments, Thomas Corpetti, Sébastien Lefèvre, 2016-2019, Dimitri Lague (CNRS, Geosciences)
  - Ahmed Samy Nassar, Learning geographic information from multi-modal imagery and crowdsourcing, 2017-2020, Sébastien Lefèvre, Jan Dirk Wegner (ETH Zurich)
  - Caglayan Tuna, Scale Spaces for Satellite Image Streams and Fast Pattern Detection, 2017-2020, Sébastien Lefèvre, François Merciol

  - Titouan Vayer, Optimal Transport for structured objects, 2017-2020, Nicolas Courty, Laetitia Chapel, Romain Tavenard

- PhD defended during the year:
  - Yanwei Cui, Kernel-based learning on hierarchical image representations: applications to remote sensing data classification, 2013-2017, Laetitia Chapel, Sébastien Lefèvre
  - Romain Huet, Sparse neural coding for a vision system, 2013-2017, Nicolas Courty, Sébastien Lefèvre

6.2.3 Juries

- Sébastien Lefèvre: PhD reviewer of Emmanuel Maggiori (Univ. Nice Sophia Antipolis)
- Sébastien Lefèvre: PhD reviewer of Francky Randrianasoa (Univ. Reims Champagne Ardennes)
- Sébastien Lefèvre: PhD reviewer of Charlotte Pelletier (Univ. de Toulouse)
- Sébastien Lefèvre: Chair of PhD defense committee of Lixuan Yang (CNAM)
- Sébastien Lefèvre: PhD committee of Amina Ben Hamida (Univ. Savoie Mont Blanc)

6.3 Popularization

- Chloé Friguet:
  - Journée “Sciences de l’ingénieur au féminin” - Auray
  - Research Talks - IUT Vannes
- Laetitia Chapel:
  - Research Talks - IUT Vannes
- Nicolas Courty:
  - Conference on Artificial Intelligence and Earth Observation during “Fête de la Science”
  - Conference organizer and presenter on “The game of Go and deep learning: an history of the recent progresses in AI” (200 participants)

7 Bibliography

Articles in referred journals and book chapters

[1] N. Audebert, B. Le Saux, S. Lefèvre, "Segment-before-Detect: Vehicle Detection and Classification through Semantic Segmentation of Aerial Images", *Remote Sensing 9*, 4, April 2017, p. page 1–18, https://hal.archives-ouvertes.fr/hal-01529624.

[2] A. Bailly, L. Chapel, R. Tavenard, G. Camps-Valls, "Nonlinear Time-Series Adaptation for Land Cover Classification", *IEEE Geoscience and Remote Sensing Letters*, 2017, https://halshs.archives-ouvertes.fr/halshs-01515283.

[3] N. Courty, R. Flamary, D. Tuia, A. Rakotomamonjy, "Optimal Transport for Domain Adaptation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017, https://hal.archives-ouvertes.fr/hal-01377220.

[4] Y. Cui, L. Chapel, S. Lefèvre, "Scalable Bag of Subpaths Kernel for Learning on Hierarchical Image Representations and Multi-Source Remote Sensing Data Classification", *Remote Sensing 9*, 3, March 2017, https://hal.archives-ouvertes.fr/hal-01672848.

[5] B. B. Damodaran, N. Courty, S. Lefèvre, " Sparse Hilbert Schmidt Independence Criterion and Surrogate-Kernel-Based Feature Selection for Hyperspectral Image Classification", *IEEE Transactions on Geoscience and Remote Sensing 55*, 4, April 2017, p. 2385–2398, https://hal.archives-ouvertes.fr/hal-01447452.

[6] B. B. Damodaran, J. Höhle, S. Lefèvre, "Attribute profiles on derived features for urban land cover classification", *Photogrammetric engineering and remote sensing 83*, 3, 2017, p. 183–193, https://hal.archives-ouvertes.fr/hal-01447454.

[7] M. Emily, C. Friguet, "Power evaluation of asymptotic tests for comparing two binomial proportions to detect direct and indirect association in large-scale studies ", *Statistical Methods in Medical Research 26*, 6, 2017, p. 2780–2799, https://hal.archives-ouvertes.fr/hal-01256507.

[8] R. Le Roux, Resseguier, T. Corpetti, N. Jgou, M. Madelin, C. Van Leeuwen, H. Qunol, "Comparison of two fine scale spatial models for mapping temperatures inside winegrowing areas", *Agricultural and Forest Meteorology 247*, 0, 2017, p. 159–169, https://hal.archives-ouvertes.fr/hal-01575344.

[9] A. Lefebvre, T. Corpetti, "Monitoring the morphological transformation of Beijing old city using remote sensing texture analysis", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 10*, 2, 2017, p. 539–548, https://hal.archives-ouvertes.fr/hal-02751881.

[10] S. Lefèvre, D. Tuia, J. D. Wegner, T. Produit, A. S. Nassaar, "Toward Seamless Multiview Scene Analysis From Satellite to Street Level", *Proceedings of the IEEE 105*, 10, October 2017, p. 1884 – 1899, https://hal.archives-ouvertes.fr/hal-01672849.

[11] M.-T. Pham, G. MERCIER, L. Bombrun, "Color Texture Image Retrieval Based on Local Extrema Features and Riemannian Distance", *Journal of Imaging 3*, 4, 2017, p. 43, https://hal.archives-ouvertes.fr/hal-01629218.

[12] Z. Zhang, R. Tavenard, A. Bailly, X. Tang, P. Tang, T. Corpetti, "Dynamic Time Warping Under Limited Warping Path Length", *Information Sciences 393*, July 2017, p. 91 – 107, https://hal.archives-ouvertes.fr/hal-01470554.

Publications in Conferences and Workshops

[13] E. Aptoula, M.-T. Pham, S. Lefèvre, "Quasi-Flat Zones for Angular Data Simplification", *in: International Symposium on Mathematical Morphology (ISMM)*, Fontainebleau, France, 2017, `https://hal.archives-ouvertes.fr/hal-01672857`.

[14] N. Audebert, A. Boulch, H. Randrianarivo, B. Le Saux, M. Ferecatu, S. Lefèvre, R. Marlet, "Deep learning for urban remote sensing", *in: Joint Urban Remote Sensing Event (JURSE)*, Dubai, United Arab Emirates, March 2017, `https://hal.archives-ouvertes.fr/hal-01672854`.

[15] N. Audebert, B. Le Saux, S. Lefèvre, "Couplage de données géographiques participatives et d'images aériennes par apprentissage profond", *in: GRETSI*, Juan-les-Pins, France, 2017, `https://hal.archives-ouvertes.fr/hal-01672870`.

[16] N. Audebert, B. Le Saux, S. Lefèvre, "Fusion of Heterogeneous Data in Convolutional Networks for Urban Semantic Labeling (Invited Paper)", *in: Joint Urban Remote Sensing Event (JURSE)*, *Joint Urban Remote Sensing Event 2017*, Dubai, United Arab Emirates, March 2017, `https://hal.archives-ouvertes.fr/hal-01438499`.

[17] N. Audebert, B. Le Saux, S. Lefèvre, "Joint Learning from Earth Observation and OpenStreetMap Data to Get Faster Better Semantic Maps", *in: EARTHVISION 2017 IEEE/ISPRS CVPR Workshop. Large Scale Computer Vision for Remote Sensing Imagery*, Honolulu, United States, July 2017, `https://hal.archives-ouvertes.fr/hal-01523573`.

[18] N. Audebert, B. Le Saux, S. Lefèvre, "Réseaux de neurones profonds et fusion de données pour la segmentation sémantique d'images aériennes", *in: ORASIS*, Colleville-sur-Mer, France, 2017, `https://hal.archives-ouvertes.fr/hal-01672871`.

[19] P. Bosilj, B. B. Damodaran, E. Aptoula, M. Dalla Mura, S. Lefèvre, "Attribute Profiles from Partitioning Trees", *in: International Symposium on Mathematical Morphology (ISMM)*, Fontainebleau, France, 2017, `https://hal.archives-ouvertes.fr/hal-01672856`.

[20] N. Courty, R. Flamary, A. Habrard, A. Rakotomamonjy, "Joint distribution optimal transportation for domain adaptation", *in: NIPS 2017*, Los Angeles, United States, December 2017, `https://hal.archives-ouvertes.fr/hal-01620589`.

[21] B. B. Damodaran, N. Courty, R. Tavenard, "Randomized Nonlinear Component Analysis for Dimensionality Reduction of Hyperspectral Images", *in: IGARSS 2017 - IEEE International Geoscience and Remote Sensing Symposium*, *International Geoscience and Remote Sensing Symposium*, p. 1–4, Houston, United States, July 2017, `https://hal.archives-ouvertes.fr/hal-01620604`.

[22] L. Faucqueur, F. Merciol, B. B. Damodaran, P.-Y. Rémy, B. Desclée, F. Dazin, S. Lefèvre, C. Sannier, "Scalable extraction of small woody features (swf) at the pan-european scale using open source solutions", *in: ESA EO Open Science*, Frascati, Italy, 2017, `https://hal.archives-ouvertes.fr/hal-01672869`.

[23] A. Lods, S. Malinowski, R. Tavenard, L. Amsaleg, "Learning DTW-Preserving Shapelets", *in: IDA 2017 - 16th International Symposium on Intelligent Data Analysis*, *Advances in Intelligent Data Analysis XVI*, *10584*, springer International Publishing, p. 198–209, London, United Kingdom, October 2017, `https://hal.archives-ouvertes.fr/hal-01565207`.

[24] A. Masse, S. Lefèvre, R. Binet, S. Artigues, P. Lassalle, G. Blanchet, S. Baillarin, "Fast and accurate denoising method applied to very high resolution optical remote sensing images", *in: SPIE Remote Sensing*, Warsaw, Poland, 2017, https://hal.archives-ouvertes.fr/hal-01672863.

[25] F. Merciol, T. Balem, S. Lefèvre, "Efficient and large-scale land cover classification using multiscale image analysis", *in: Big Data from Space*, Toulouse, France, 2017, https://hal.archives-ouvertes.fr/hal-01672868.

[26] J. Mifdal, B. Coll, N. Courty, J. Froment, B. Vedel, "Hyperspectral and Multispectral Wasserstein Barycenters for Image Fusion", *in: IGARSS 2017*, Houston, United States, July 2017, https://hal.archives-ouvertes.fr/hal-01620601.

[27] M.-T. Pham, S. Lefèvre, E. Aptoula, B. B. Damodaran, "Classification of VHR remote sensing images using local feature-based attribute profiles", *in: IGARSS 2017*, Fort Worth, United States, July 2017, https://hal.archives-ouvertes.fr/hal-01588290.

[28] M.-T. Pham, G. MERCIER, E. Trouvé, S. Lefèvre, "SAR image texture tracking using a pointwise graph-based model for glacier displacement measurement", *in: IGARSS*, Fort Worth (TX), United States, 2017, https://hal.archives-ouvertes.fr/hal-01672861.

[29] R. Tavenard, S. Malinowski, L. Chapel, A. Bailly, H. Sanchez, B. Bustos, "Efficient Temporal Kernels between Feature Sets for Time Series Classification", *in: European Conference on Machine Learning and Principles and Practice of Knowledge Discovery*, Skopje, Macedonia, September 2017, https://halshs.archives-ouvertes.fr/halshs-01561461.

Miscellaneous

[30] R. Fablet, N. Bellec, L. Chapel, C. Friguet, R. Garello, P. Gloaguen, G. Hajduch, S. Lefèvre, F. Merciol, P. Morillon, C. Morin, M. Simonin, R. Tavenard, C. Tedeschi, R. Vadaine, "Next Step for Big Data Infrastructure and Analytics for the Surveillance of the Maritime Traffic from AIS & Sentinel Satellite Data Streams", BiDS' 2017 - Conference on Big Data from Space, November 2017, Poster, https://hal.inria.fr/hal-01671323.

[31] M. Laroze, R. Dambreville, C. Friguet, S. Lefèvre, E. Kijak, " Active learning for object detection", Statlearn'17 - Challenging problems in statistical learning, 2017, Poster, https://hal.inria.fr/hal-02639924.