Project-Team OBELIX

Environment Observation through Complex Imagery

Vannes & Rennes

Activity Report

2014

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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.

2.2 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.

3 Scientific Foundations

3.1 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 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.,

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

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 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

[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.

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 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,

[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.

[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.

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 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

[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.

[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.

computation of such distances could be used at the core of machine learning algorithms so as to trade accuracy for efficiency.

3.2 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 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 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

[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.

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.

3.3 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 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

[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.

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.

4 New Results

4.1 Morphological image analysis

Participants: Sébastien Lefèvre, Luc Courtrai, Nicolas Courty.

Mathematical Morphology is a rich framework for image processing. It consists in non-linear operators that take into account the spatial information contained in the image. While most of these operators have been defined on binary and grayscale images, their extension to color and other multivariate (e.g., multispectral) data is not straightforward. We have contributed to the general knowledge in the field through a dedicated book chapter [9] related to morphological template matching in color images. Furthermore, we have more specifically addressed the problem of ordering pixels in hyperspectral images based on their distances to end-members (published in ICIP 2014 [11]), from which more relevant morphological features can be derived. Finally, we have also extended a morphological filter called path opening to process images at the region level instead of the pixel level. Coupled with a region-based hit-or-miss transform, it allows to derive an efficient and robust method for road extraction from satellite images, that has been published in the IAPR Workshop on Pattern Recognition in Remote Sensing 2014 [18].

4.2 Hierarchical image analysis

Participants: Sébastien Lefèvre, François Merciol, Laetitia Chapel, Petra Bosilj.

Hierarchical representations provide a powerful way to model, analyze and process images and other visual data (e.g. videos). The team has continue to explore how to such trees using ancillary data that are often available when processing hyperspectral images. New algorithms are available for α-trees (published in IIM 2014 [19]) and (α, ω)-trees (published in WHISPERS 2014 [17]) that respectively involve only local and both local and global constraints. The latter also solves the issue related to the definition of the global range constraint on multivariate data. The resulting trees are better fitting the content of the image, and as such lead to more relevant image features and subsequent land cover classification.

4.3 Manifold learning

Participants: Nicolas Courty, Laetitia Chapel, Sébastien Lefèvre.

Matrix Factorization.We have proposed a new non-negative matrix factorization technique called SAGA (Sparse and Geometry Aware Matrix Factorization). SAGA (1) allows the decomposition of the original data on multiple latent factors accounting for the geometrical structure of the manifold embedding the data; (2) provides an optimal representation with a controllable level of sparsity; (3) has an overall linear complexity allowing handling in tractable time large and high dimensional datasets. It operates by coding the data with respect to local neighbors with non-linear weights. This locality is obtained as a consequence of the simultaneous sparsity and convexity constraints. This work was done in collaboration with Thomas

Burger (CNRS/CEA Grenoble), Gong Xing (NLPR Beijing) and Jimmy Vandel (CNRS/CEA Grenoble), and has been published in the Machine Learning Journal [4].

Classification, and anomaly detection.The team has pursue its activities in the field of classification of remote sensing, and focused on manifold learning for classwise manifold representation and classification. A paper showing promising results w.r.t. standard SVM on hyperspectral images was published in the special issue "Machine Learning for Remote Sensing Data Processing" of IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing [3]. The same kind of representation was also used to derive a new and efficient anomaly detection technique that has been published in ECML/PKDD 2014 [13].

4.4 Domain adaptation

Participants: Nicolas Courty.

In the context of remote sensing, re-using models trained on a specific image acquisition to classify landcover in another image is no easy task. Illumination effects, specific angular configurations, abrupt and simple seasonal changes make that the spectra observed, even though representing the same kind of surface, drift in a way that prevents a non-adapted model to perform well. From 2014, we have started to work on this problem, known as the Domain Adaptation problem in the machine learning community.

Graph matching. One of our first work in this direction was performed in collaboration with Devis Tuia (researcher in EPFL at this time). We proposed a new correlated correspondence algorithm based on network analysis. The algorithm finds a matching between two distributions, which preserves the geometrical and topological information of the corresponding graphs. We evaluated the performance of the algorithm on a shadow compensation problem in hyperspectral image analysis: the land use classification obtained with the compensated data is improved. This paper was published in ICPR [20].

Optimal transport. 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), and Alain Rakotomamonjy (University of Rouen, LITIS) and has led to three publications [14, 16, 15].

4.5 Coupling data and models

Participants: Thomas Corpetti, Pascal Zille, Gong Xing.

Multiscale models for motion estimation. In the context of optical flow, multi-resolution frameworks, often based on coarse-to-fine warping strategies, are widely used by state-of-the-art methods. They allow the recovery of large motions by successive estimations of the flow field at several resolution levels. Although such approaches perform very efficiently and usually lead to faster minimizations, they generally consider independent problems at each resolution levels and do not exploit the existing interactions between scales (especially the influences of fine scales on larger ones). We have work on this issue by proposing a flexible framework, inspired from fluid mechanics, able to partly counter these limitations. For each resolution level, our process filters the equations of interest and decomposes the key variables into resolved (i.e. at a given resolution) and unresolved (i.e. at finer resolutions) components. This enables to derive a new data term that takes into account, at coarse resolutions, the influence of their unresolved parts. From this new term, we also have proposed different estimation strategies, depending on whether we explicitly know the type of relations between the different scales (as for physical processes) or not. This work was done in collaboration with Shao Liang (Ecole Centrale Lyon) and Cui GuiXiang (Tsinghua University, Beijing) and has been published in [10] in 2014.

Estimation of biophysical variables using plant growth models. The monitoring of Leaf Area Index (LAI) time series in intense agriculture areas is a key issue in order to evaluate relationships between agriculture practices and environment quality. To this end, medium resolution remote sensing data (such as MODIS of future SENTINEL) are interesting to observe in a more or less continuous time (one image every day) the evolution of landscapes. However in practice, a frame-by-frame estimation of LAI from images is unsatisfactory since the quality of each single data is subjected to undesirable effects due to atmosphere disturbance, lighting conditions, shooting angle, ... yielding a lack of temporal consistency of resulting time series. We have proposed an approach to recover time consistent series of LAI from noisy and sometimes corrupted sequential remote-sensing data. It combines the prior information of a plant growth model, namely GreenLab developed in Chinese Academy of Sciences, and low quality remote sensing observations using stochastic data assimilation techniques. This results in a complete system where we not only recover consistent LAI but thanks to the physical model, we also recover LAI issued from various organs (Leaf, branch, fruits, ...). This work has been done in collaboration with Chinese Academy of Sciences and is in revision in IEEE Transactions on Geosciences and Remote Sensing.

4.6 Change detection and time series analysis

Participants: Thomas Corpetti, Nicolas Courty, Romain Tavenard, Pauline Dusseux, Gong Xing.

Time series analysis for grassland monitoring From a thematically point of view, the analysis of grassland systems and the way they are managed is a very hot point of view of the impact of grasslands in environment is important. Therefore, High Spatial Resolution (HSR) remote sensing time series are of prime importance to monitor grassland systems. However, because of the complexity of the resulting time series, the identification of various practices using conventional tools is no easy task. Several studies have been done, using different metrics to compare time series, to compare, cluster and classify remote sensing time series for grassland systems. These works have been published in 4 journal papers [2, 5, 6, 7] and one conference [12] in 2014.

5 Contracts and Grants with Industry

5.1 Egide, Cai YuanPei (2012–2014)

Thomas Corpetti acted as coordinator for the Urba-Pol project on urban pollution prediction. This project gathers OSUR and University of Beihang (China) with a funding of 25 k€.

5.2 ANR, Jeunes Chercheurs (2013–2017)

Sébastien Lefèvre acted as coordinator for the ASTERIX project on spatio-temporal analysis by recognition within complex images for remote sensing of environment. This project gathers IRISA, OSUR, LIVE and IPGS (Strasbourg), DYNAFOR (Toulouse) with a funding of 275 k€.

5.3 CNES, TOSCA (2014–2017)

Thomas Corpetti acted as coordinator for the VEGIDAR project on urban vegetation analysis by coupling very high resolution optical remote sensing and Lidar data. This projects gathers IRISA, LETG (Rennes), Lab-STICC (Brest), IGN (Paris) and LIVE (Strasbourg) with a funding of 150 k€.

5.4 International Space Science Institute / ISSI Beijing, international team (2014–2016)

Thomas Corpetti acted as coordinator for the RESIDUAL project on remote sensing image data assimilation for pollution monitoring: application to urban and ocean pollution. This project gathers IRISA, INRIA (Rennes & Grenoble), LMBA (Vannes), LSCE (Paris), Florida State University (USA), Harbin Institute of Technology (China), Tsinghua University (China), Vietnamese Academy of Science (Vietnam), Russian Academy of Sciences (Russia) with a funding of 98 k€.

5.5 Labex Comin Labs (2013–2016)

Nicolas Courty and Sébastien Lefèvre contribute to the SENSE project on sparse neural coding and bionic vision system. This project gathers IRISA and Lab-STICC (Lorient & Brest) with a team funding of 105 k€ (global funding: 414 k€).

5.6 UBS, PPI program (2013–2017)

Sébastien Lefèvre and Luc Courtrai contribute to the Littoralg project on coastal monitoring and seaweed valorisation. This project gathers several labs from UBS (IRISA, GMGL, LBCM, Geoarchitecture, IREA, CRPCC) with a team funding of 48 k€ (global funding: 297 k€).

5.7 ACT-TER Chair (2013–2014)

Public/private partnership aiming to foster new models of knowledge extraction for local policies and stakeholders. A contract of 25 k€ has been signed to develop an information and knowledge exchange platform supporting public decision making, by sharing heterogeneous data (text, images, statistics) in various domains (public organisations as well as private operators).

5.8 WIPSEA (2014–)

SME located in Rennes aiming to deliver imaging solutions for wildlife monitoring. A contract of 20 k€ is being signed to support the R&D activity of WIPSEA in the field of marine image analysis and processing.

5.9 MGDIS (2013–2016)

SME located in Vannes aiming to deliver software solutions to public authorities for decision making. A contract of 7.5 k€ has been signed to study how aerial and satellite images can provide ancillary knowledge to complement existing data sources.

6 Other Grants and Activities

6.1 International Collaborations

- Okan University, Istanbul, Turkey: Erchan Aptoula (Associate Professor) is collaborating with the team on several topics, mainly related to color and hyperspectral image analysis with mathematical morphology [9, 11].

- EPFL, Lausanne and University of Zurich, Switzerland: Nicolas Courty spent 2 months at EPFL in 2014 as invited professor. Joint works have been initiated with Devis Tuia (who moved from EPFL to University of Zurich during Fall 2014) on several topics, mainly related to domain adaptation and machine learning [20, 15].

- Uppsala University, Sweden: Cris Luengo (Associate Professor) and Vladimir Curic (PhD student) visited OBELIX for 10 days (Frö grant) and one month (UBS grant) in June 2014 respectively. Some joint work have been initiated on adaptive mathematical morphology.

- ITC / University of Twente, Netherlands: Norman Kerle (Associate Professor) visited OBELIX for one week (UBS grant) in Spring 2014. Joint works have been initiated on geographic object-based image analysis.

- University of Groningen, Netherlands: Petra Bosilj (PhD candidate in OBELIX) spent 3 months in the team of Michael Wilkinson (Associate Prof.) with financial supports from UEB, CNRS, and French Embassy. A joint work was initiated on image description based on morphological trees.
- University of Tromsø, Norway: Robert Jenssen (Associate Prof.) visited OBELIX for a week in 2014 (UBS grant). Topics for joint works are currently being explored.
- Chinese Academy of Sciences, Institute of Automation and Institute of Remote Sensing and Applications. In the context of LIAMA (Sino-French Lab in Computer Sciences in Beijing), Thomas Corpetti is heading a research group entitled CARIOCA[1] which associates 3 chinese and 3 french researchers. During this period, one french PhD in co-supervision and one chinese PhD in co-tutelle (P. Zille and X. Gong, PhD respectively defended in Nov. 2014 and Jan. 2015) stayed one year in their foreign country. This activity is supported by CNRS and various contracts (see above).

6.2 National Collaborations

- University of Grenoble-Alpes, CEA (iRTSV/BGE), INSERM (U1038), CNRS (FR3425) through a collaboration with Thomas Burger (CR CNRS)
- University of Lorraine / CNRS, LORIA (UMR 7503) through a collaboration with Jonathan Weber (MCF U. Lorraine) [9]
- ESIEE / CNRS, LIGM (UMR 8049), through a collaboration with Benjamin Perret (MCF. ESIEE) [9]
- TEXMEX team from INRIA/IRISA, through a collaboration (PhD cosupervision) with Ewa Kijak (MCF U. Rennes 1)
- University of Nice / Observatoire de la côte d'Azur: collaboration with Rémi Flamary [14, 16, 15]
- Ecole Centrale Lyon: collaboration with Shao Liang, co-supervision of the PhD of Pascal Zille and Xu Chen

7 Dissemination

7.1 Scientific Responsibilities and Involvement in the Scientific Community

- Sébastien Lefèvre serves as the deputy head of the doctoral school SICMA (head for UBS). He leads the team project OBELIX. He was organizing the special session "image retrieval in remote sensing" during CBMI 2014. He is a member of various program committee for international (ICISP, VISAPP, IIM) and national (EGC) conferences and

[1]Climate and lAnd coveR InteractiOns with Complex datA, `http://liama.ia.ac.cn/research/liama-projects/`

serves as regular reviewer in international journals (IEEE Journal of Selected Topics on Applied Earth Observations and Remote Sensing, IEEE Transactions on Geosciences and Remote Sensing, IEEE Transaction on Image Processing) and conferences (ICASSP, ICIP, IGARSS). He was holder of the mobility grant Blåtand and has given seminars in University of Copenhagen, Technical University of Denmark, IT University of Copenhagen, and University of Aarhus in Denmark. He was reviewer for 2 doctoral theses (U. Paris Descartes and U. Lorraine). He serves as an expert for French Ministry of Research (CIR/JEI) and A*MIDEX Excellence Cluster.

- Thomas Corpetti is animating the CARIOCA action in LIAMA, Beijing (see above for details). In Rennes, he is in charge of the image analysis platform of OSUR (Observatory for Universe Sciences of Rennes) which aims at proposing the access, either inside OSUR or to the entire research community, to the computer vision techniques developed in the various groups of OSUR (and in particular OBELIX). In this context, he has led the answer to the CPER call related to the "numerical tools for environment" axis where a larger platform, entitled LOVE (french acronym for "Virtual Observatory for Environment"), will be developed and will embed analysis, modelisation and visualization tools. For this activity, he is a member of the direction team of OSUR. He is a regular reviewer of IEEE (Image Processing, Geosciences and Remote Sensing, Selected Topics in Applied Earth Observations and Remote Sensing) and other related journals (Remote Sensing for Environment, Experiments in Fluid, Journal of Mathematical Imaging and Vision). He has been reviewer of IEEE ICIP (International Conference on Image Processing) and has been reviewer of 5 PhDs (Liyun He-Guelton –Telecom Bretagne, Brest, Vincent Chabot – INRIA Grenoble, Rihab Mechri – LSCE, Laboratoire des Sciences du Climat et de l'Environnement, Viateur Tuyisenge, Univ. Clermont Ferrand, Ludovic Magerand, Univ. Clermont-Ferrand). He also was in the committee of 2 PhD (Jonas Lambert, Toulouse, and Yin Yang, INRIA Rennes, where he was president of the committee). Finally, he co-organized two scientific animations days with approx. 50 people per day (Data assimilation on January 2014 and LIDAR in April 2014).

- Nicolas Courty co-leads the team project OBELIX. He served as regular reviewer in international journals (IEEE trans on Visualization and Computer Graphics, IEEE trans. on Multimedia, IEEE Signal Processing Letters, JSTAR) and conferences (Whispers, CBMI). He served as an expert for the evaluation of the projects of the 'Image and Networks' pôle de compétitivité. He was reviewer for 1 doctoral theses (Antoine Fagette, UPMC in Paris).

7.2 Teaching

- Laetitia Chapel teaches statistics at the statistical department of IUT Vannes.

- Thomas Corpetti has taught 24h in Machine Learning in ENS Rennes (2014) and 20h in GIS and Image processing (ArcGis 10 / Python), Univ. Rennes II, in 2014.

- Luc Courtrai teaches various computer science courses at Licence and Master level.

- Nicolas Courty teaches computer graphics and multimedia coding in the second year of the Master Web, Image and Networks of UFR SSI.
- Sébastien Lefèvre teaches programming, software engineering, and multimedia at the computer science department of IUT Vannes. He is in charge of the 1st year coding projects.
- François Merciol teaches system and network administration and programming at the computer science department of IUT Vannes.
- Romain Tavenard teaches programming, data mining, databases and the basics of computer science at Univ. Rennes II, where he is deputy director of the statistics department.

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