Automatic Creation of Maps by Using Multiple Data Sensors

Edemir Ferreira Jr, Arnaldo de A. Araújo, Jefersson A. dos Santos
Department of Computer Science, Universidade Federal de Minas Gerais (UFMG)
Belo Horizonte, Brazil

***Abstract*—An usual way to acquire information about monitored objects or areas in earth surface is by using remote sensing images. These images can be obtained by different types of sensors (e.g., active and passive) and according to the sensor, distinct properties can be observed from the specified data. Typically, these sensors are specialized to encode one or few properties from the object (e.g. spectral and spatial properties), which makes necessary the use of diverse and different sensors to obtain many complementary information as possible. Given the amount of information collected, it is essential to use a capable technique to combine accordingly the different characteristics obtained. The objective of this work, which is in progress, is the development of a framework able to exploit the diversity of these different types of features, extracted from different sensors, to achieve high degrees of accuracy in the creation of thematic maps for the classification task.**

***Keywords*-Data fusion; remote sensing; ensemble of classifiers; mapping;**

I. Introduction

Over the years, there has been a growing demand for remotely-sensed data. Specific objects of interest are being monitored with earth observation data, for the most varied applications. Examples include ecological science (estimating biomass, biodiversity, land cover changes) [1], geology (recovering physicochemical mineral properties such as composition and abundance) [2], hydrological science (changes in wetland characteristics, water quality and others) [3], agriculture (classifying crops and for precision agriculture) [4], military (target detection using spectral information) [5], and many other applications.

Remote sensing images (RSIs) have been used as a major source of data, particularly with respect to the creation of thematic maps. This process is usually modeled as a supervised classification problem where the system needs to learn the patterns of interest provided by the user and assign a class to the rest of the image regions. In the last few decades, the technological evolution of sensors has provided remote sensing analysts with countless distinct information, e.g., spatial, spectral, temporal, thermal.

Typically, these sensors are designed to be specialists in obtaining one or few properties from the earth surface. Therefore, it is necessary the utilization of diverse and different sensors to gather the most complementary information as possible. In this scenario, it is essential to use a more suitable technique to combine the different features in a effective way. Mura et al. [6] confirmed the benefit of the use of data fusion in the challenges associated with RSI analysis in competitions. They pointed out that it is difficult to conclude which method has the best performance, since it depends on the foundation of the problem and the nature of the data used.

In this work in progress, we are developing a method capable of receiving several data from different sensors and combining them for the task of classification in a general scenario. Our method is based in the framework proposed by [7]. Our efforts are focused in adapting that framework in order to handle with an input of one very high spatial (VHS) resolution image and one hyperspectral (HS) resolution image. Our intent is to create a late fusion-based approach for automatic creation of thematics maps by fusioning the most suitable classifiers.

II. Related work

Despite the recent advances in feature extraction and representation for RSIs, the combination/fusion of these features, especially when they are extracted by different sensors, requires the development of new techniques.

In this context, Li et al. [8] developed a classification technique based on active learning to combine spatial and spectral information. Petitjean et al. Yang et al. [10] presented a system for evaluating the growth of crops using high resolution images from satellites and airplanes. An approach using genetic algorithm to the combination of features/learning methods based on spatial and spectral data, was proposed by Santos et al. [11] to create thematics maps. Ouma et al. [12] and Wang et al. [13] showed approaches that use multi-scale data to identify land use changes. In Ouma et al. [12], the authors presented a multi-scale segmentation technique with a neural network (unsupervised) for analysis of vegetation. Wang et al.[13] in the other hand, proposed an approach to change detection in urban areas. That method is based on the fusion of characteristics from multiple scales through the average pixel of each scale. The result is a new image corresponding to the combination of scales.

More recently, Gharbia et al. [14] made an analysis of fusion techniques images (Intensity-Hue-Saturation (IHS), Brovey Transform (BT), Principle Component Analysis (PCA)) for remote sensing tasks, at pixel level, showing that all techniques have limitations when used individually. They encourage the use of hybrid systems as a solution.

Mura et al. [6] analyzed the approaches used in the past nine years of data fusion competition (Data Fusion Contest). The approaches are separated into three main categories: the level of information/pixels, where the data are combined in the way they were extracted; feature level, where the data are extracted and used as entries for a classification model; and the decision level, which uses a combination of different outputs from various sources, to increase the robustness of final decision (using, e.g., a majority vote). After investigated the last challenges, Mura et al. confirmed the benefits of the use of data fusion in the challenges associated with RSI analysis in competitions. In the majority of cases, the frameworks proposed in the literature are projected to deal with a specific scenario or a particular region, using techniques apart of each domain and object, e.g., roofs are checked with shape features, tree and vegetation are discriminated using a vegetation index. However, it is very difficult to conclude what is the best approach, since it depends on the foundation of the problem, the nature of the data used and the source of information utilized.

The method we propose in this work aim at exploiting multi-sensor data in a more general way. We intend to propose a framework based on a supervised learning scheme, dealing with different scenarios, regions and objects, on the creation of thematic maps (classification task).

III. Methodology

A. Overview

The proposed framework is projected to receive two images from the same place with different domains as input: an image with very high spatial (VHS) resolution and another one with hyperspectral (HS) resolution.

In order to describe our methodology, we divided the procedure in three main parts: segmentation, feature extraction and classification.

In the segmentation phase, given the VHS and HS images of training set we begin with a segmentation method in the spatial domain for the purpose of splitting the entire image in small objects to be analyzed in a region based method afterward, see Fig. 1.

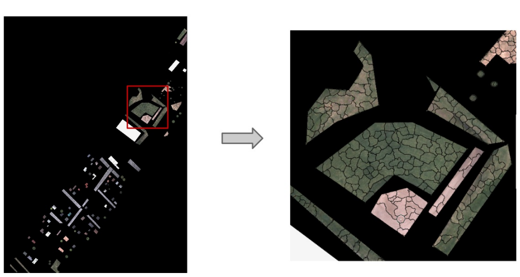

Fig. 1. Segmented training data in small objects to be analyzed in a region based method.

In the spectral domain, all the values of the image are used in a pixel based method, stacking the reflectance values of each pixel in a vector, see Fig. 2.

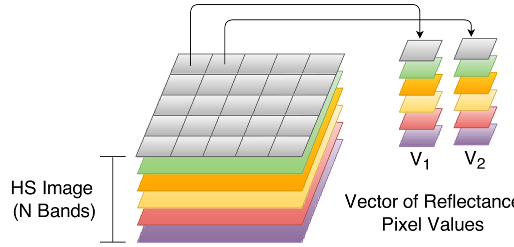

Fig. 2. Stacking the reflectance values of each pixel.

At the feature extraction phase, in spatial domain, we have used image descriptors based on color information and texture information to extract complementary features of the regions. In spectral domain, we used different source of features from dimensionality reduction/projection methods.

In the classification phase, a validation set was split from the training set and several learning models was fitted, using the features extracted by each descriptors, resulting in an amount of classifiers (tuples of descriptor/learning method) which was used to learn the probability distribution of the training set.

Given the amount of classifiers trained using different features from spatial and spectral domain, and evaluated in the validation set, the learned knowledge pass to a process of selection of tuples, which uses measures of diversity [15] between classifiers to calculate the degree of correlation/decorrelation between the tuples which could improve the framework posteriorly.

However, since the selection process was based in [7], we adapted the framework proposed in [7] to receive images from different domains and resolutions. For this we applied a mapping between the spatial and spectral data, using an interpolation method.

Once the best classifiers are selected, the same method of segmentation is used in the test set, and the segmented objects are labeled by the best classifiers as regions (spatial tuple) or pixel by pixel (spectral tuple) creating a thematic map for each classifier.

Finally the thematic maps are used as input of a late fusion technique, that takes the final decision regarding the definition of the regions classes (Fig. 3).

B. Formalization

Let $\mathtt{D_{VHS}}$ and $\mathtt{D_{HS}}$ be the VHS and HS domains. Let L be any set of learning methods and let F_{VHS} and F_{HS} be a set of feature extraction methods of $\mathtt{D_{VHS}}$ and $\mathtt{D_{HS}}$ respectively.

Suppose that classifiers are created by combining each available learning method with each image descriptor of all domains.

a) Segmentation: Let S be any image segmentation algorithm and let G be an image, containing $|G|$ regions, where the class of each region $g_i \in G$, $(1 < i \leq |G|,\ i \in \mathbb{N}^*)$ is known.

Initially, the image G is segmented using S, resulting in $|g_{(i,r)}| \subseteq G$ subregions, where $g_{(i,r)}$ is a subregion r of g_i

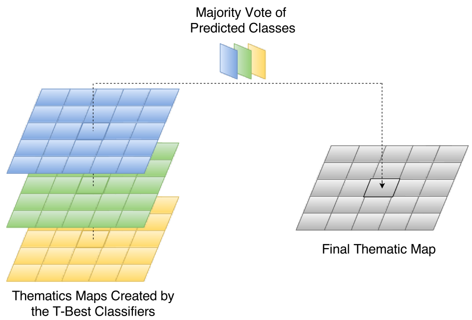

Fig. 3. Thematic Maps of the T-best tuples and the Final Thematic Map.

$(1 \leq r \leq |g_i|)$. See Fig. 1.

The subregions $g_{(i,r)}$ is used to construct both, the training (T) and validation (V) sets, where $T \cup V = G$ and $T \cap V = \emptyset$. As we consider a supervised learning scenario, the actual classes for training and validation data subregions are known a priori.

b) Feature Extraction: The features from the subregions $g_{(i,r)}$ of T and V are extracted using F_{VHS} and F_{HS}.

In the spatial domain, is used a region based method at the subregions $g_{(i,r)}$ Fig. 1.

In the spectral domain, is used all the values of a subregion $g_{(i,r)}$ in a pixel based method, stacking the reflectance values of each pixel in a vector, see Fig. 2.

c) Classification: At the beginning, all the learning methods are trained in both domains, using the features extracted of the set T, creating the classifiers $c_j \in C$, $(1 < j \leq |C|$, $j \in \mathbb{N}^*)$. Thereupon, the outcome of each classifier from $\mathtt{D_{VHS}}$ and $\mathtt{D_{HS}}$, on the validation set V, is computed and stored into a matrix M_v, where $M_v = |V|$ x $|C|$.

Since the inputs from $\mathtt{D_{VHS}}$ and $\mathtt{D_{HS}}$ have different resolutions, a mapping between them is made using a interpolation method.

In the following, M_v is used as input to select a set $C^* \subseteq C$ of classifiers that are good candidates to be combined. This selection is made using diversity measures between the classifiers as in [7].

Given a new image I, is applied the segmentation method S in I, generating regions $i_k \in I$, and every trained classifier from C^* is used to predict the classes of i_k, producing M thematic maps, one for each $c_j^* \in C^*$.

The M thematic maps created are used as input of a late fusion technique, that takes the final decision regarding the definition of the class of each region $\mathtt{i_k}$.

IV. Experiments

In the experiments, we aim at showing the performance regarding the effectiveness, in terms of evaluation measures, and efficiency of the selection method used in the proposed approach.

The method was compared with some other methods as baselines: **Spatial** and **Spectral** are baselines utilizing almost the same workflow described in methodology, but using only one domain, spatial or spectral. **Spatial+Spectral** is a baseline using the majority vote of **Spatial** and **Spectral** baselines. The **Our Approach** is our approach described in methodology.

A comparison of all methods, using evaluation measures, with the confidence intervals, is showed in Fig. 4 and Fig. 5.

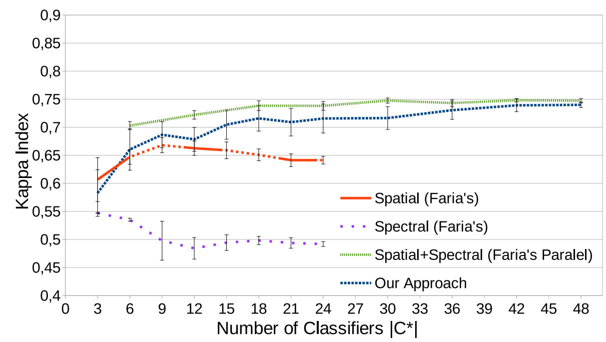

Fig. 4. Kappa Index

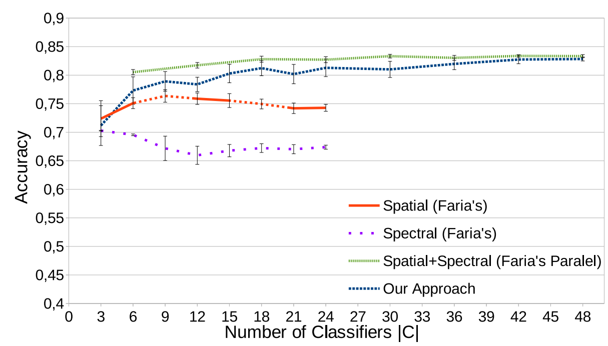

Fig. 5. Accuracy Index

A. Setup

For the evaluation of our method, was used the dataset grss_dfc_2014 [16] of the Data Fusion Contest 2014, provided by Telops Inc.(Canada), having two sensors information, Very High Spatial (VHS) resolution and Hyper Spectral (HS) resolution, used in a urban classification scenario.

We validate our experiments through two different evaluation measures: Accuracy and Kappa index. For the statistical test of significance, we use paired Student's t-test (confidence of 95%), using 10 samples for each experiment, since in a statistical way that will still provide the desired confidence for our experiments [17].

Some important parameters are used in the methodology. For the segmentation, in the training and test sets, we used the IFT-Watershed with spatial radius 5 and volume threshold equal to 100.

For the feature extraction, in spatial domain, we used 4 image descriptors: three of them based in color information, Border/Interior Pixel Classification (BIC) [18], Color

Coherence Vector (CCV) [19] and Global Color Histogram (GCH)[20], and one based in texture information, Unser [21]. In spectral domain, is utilized four different source of features: the raw data of HS image (84 Bands), the first 3 and 4 principal components of Principal Component Analysis (PCA) [22], and the Fisher Linear Discriminant (FLD) [23] components.

In the processing phase, a validation set is split from training set and trained in a Stratified ShuffleSplit cross validation scheme, using a group of 6 weak learners: Gaussian Naive Bayes, 3-Nearest Neighbors, 5-Nearest Neighbors, 10-Nearest Neighbors, Decision Tree, and a Support Vector Machine with linear kernel, using the features extracted by each descriptors, resulting in the total of 48 tuples (descriptor/classifier, 24 from each domain).

We have used the implementation of those learning methods available in the Scikit-Learn Python library [24]. All learning methods were used with default parameters which means we did not optimize them whatsoever. The management of HS data are made using the Spectral Python (SPy) Library, including the extraction of features from spectral domain.

B. Results and Discussion

We performed the above-mentioned experiments and got some interesting results. The comparison shows that except the **Spatial+Spectral**, there is no statistical significant difference among our approach and other baselines when the number of classifiers is less than 15. It is also visible the impact of the fusion of features from the VHS and HS domain, achieving better results in both measures analyzed.

Another interesting point, observed in our experiments, is the drawback of the majority vote fusion when just a single domain is used, decreasing the results obtained in some cases.

The results also show that the **Spatial+Spectral** obtained the best results in our experiments, presenting stability, dealing with the drawback of majority vote fusion, but not statistical significance among the proposed method in the most of cases.

V. Conclusion

In this paper, we introduced a method to deal with a generic scenario of classification in remote sensing, using a scheme of selection of features and classifiers from different domains, and fusioning the predict results in a final thematic map. We used the dataset grss_dfc_2014 [16] of the Data Fusion Contest 2014, for the evaluation of the framework, using a statistical test, and we obtained a significant improvement in relation of two of three baselines proposed. For the future work, we want to extend this framework exploring the use of more descriptors, classifiers, and other fusions methods.

Acknowledgements

The authors would like to thank Telops Inc. (Québec, Canada) for acquiring and providing the data used in this study, the IEEE GRSS Image Analysis and Data Fusion Technical Committee and Dr. Michal Shimoni (Signal and Image Centre, Royal Military Academy, Belgium) for organizing the 2014 Data Fusion Contest, the Centre de Recherche Public Gabriel Lippmann (CRPGL, Luxembourg) and Dr. Martin Schlerf (CRPGL) for their contribution of the Hyper-Cam LWIR sensor, and Dr. Michaela De Martino (University of Genoa, Italy) for her contribution to data preparation.

References

[1] A. Ghiyamat and H. Z. Shafri, "A review on hyperspectral remote sensing for homogeneous and heterogeneous forest biodiversity assessment," *IJRS*, vol. 31, no. 7, pp. 1837–1856, 2010.

[2] E. Cloutis, "Review article hyperspectral geological remote sensing: evaluation of analytical techniques," *IJRS*, vol. 17, no. 12, pp. 2215–2242, 1996.

[3] T. Schmid, M. Koch, and J. Gumuzzio, "Multisensor approach to determine changes of wetland characteristics in semiarid environments (central spain)," *TGRS*, vol. 43, no. 11, pp. 2516–2525, 2005.

[4] Y. Lanthier *et al.*, "Hyperspectral data segmentation and classification in precision agriculture: A multi-scale analysis," in *IGARSS 2008*, vol. 2. IEEE, 2008, pp. II–585.

[5] X. Briottet *et al.*, "Military applications of hyperspectral imagery," in *SPIE*. International Society for Optics and Photonics, 2006, pp. 62 390B–62 390B.

[6] M. D. Mura, S. Prasad, F. Pacifici, P. Gamba, and J. Chanussot, "Challenges and opportunities of multimodality and data fusion in remote sensing," in *EUSIPCO*, 2014, pp. 106–110.

[7] F. A. Faria, J. A. Dos Santos, A. Rocha, and R. d. S. Torres, "A framework for selection and fusion of pattern classifiers in multimedia recognition," *PRL*, vol. 39, pp. 52–64, 2014.

[8] J. Li, J. M. Bioucas-Dias, and A. Plaza, "Spectral–spatial classification of hyperspectral data using loopy belief propagation and active learning," *TGRS*, vol. 51, no. 2, pp. 844–856, 2013.

[9] F. Petitjean, C. Kurtz, N. Passat, and P. Gançarski, "Spatio-temporal reasoning for the classification of satellite image time series," *PRL*, vol. 33, no. 13, pp. 1805–1815, 2012.

[10] C. Yang *et al.*, "Using high-resolution airborne and satellite imagery to assess crop growth and yield variability for precision agriculture," *Proceedings of the IEEE*, vol. 101, no. 3, pp. 582–592, 2013.

[11] A. B. Santos, A. de Albuquerque Araújo, and D. Menotti, "Combining multiple classification methods for hyperspectral data interpretation," *J-STARS*, vol. 6, no. 3, pp. 1450–1459, 2013.

[12] Y. O. Ouma, S. Josaphat, and R. Tateishi, "Multiscale remote sensing data segmentation and post-segmentation change detection based on logical modeling: Theoretical exposition and experimental results for forestland cover change analysis," *Computers & geosciences*, vol. 34, no. 7, pp. 715–737, 2008.

[13] W.-j. Wang, Z.-m. Zhao, and H.-q. Zhu, "Object-oriented change detection method based on multi-scale and multi-feature fusion," in *JURSE, 2009 Joint*. IEEE, 2009, pp. 1–5.

[14] R. Gharbia, A. T. Azar, A. E. Baz, and A. E. Hassanien, "Image fusion techniques in remote sensing," *arXiv preprint arXiv:1403.5473*, 2014.

[15] L. I. Kuncheva and C. J. Whitaker, "Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy," *JMLR*, vol. 51, no. 2, pp. 181–207, 2003.

[16] "2014 ieee grss data fusion contest. online. : http://www.grss-ieee.org/community/technical-committees/data-fusion/."

[17] R. Jain, "The art of computer systems performance analysis," 1981.

[18] R. O. Stehling, M. A. Nascimento, and A. X. Falcão, "A compact and efficient image retrieval approach based on border/interior pixel classification," in *CIKM*. ACM, 2002, pp. 102–109.

[19] G. Pass, R. Zabih, and J. Miller, "Comparing images using color coherence vectors," in *ACM Multimedia*. ACM, 1997, pp. 65–73.

[20] M. J. Swain and D. H. Ballard, "Color indexing," *IJCV*, vol. 7, no. 1, pp. 11–32, 1991.

[21] M. Unser, "Sum and difference histograms for texture classification," *TPAMI*, no. 1, pp. 118–125, 1986.

[22] I. Jolliffe, *Principal component analysis*. Wiley Online Library, 2002.

[23] R. A. Fisher, "The use of multiple measurements in taxonomic problems," *AE*, vol. 7, no. 2, pp. 179–188, 1936.

[24] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *JMLR*, vol. 12, pp. 2825–2830, 2011.