Toward Multi-Scale Object-Based Data Fusion

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Abstract. This paper proposes a new methodology for object based 2-D data fu- sion, with a multiscale character. This methodology is intended to be use in agriculture, specifically in the characterization of the water status of different crops, so as to have an appropriate water management at a farm-holding scale. As a first approach to its evaluation, vegetation cover vigor data has been integrated with texture data. For this purpose, NDVI maps have been calculated using a multispectral image and Lacunarity maps from the panchromatic image. Preliminary results show this methodology is viable in the integration and management of large volumes of data, which characterize the behavior of agricultural covers at farm-holding scale.

Keywords. data fusion, multi-scale analysis, decision trees, fusion rules.

1. Introduction

Today, there is a plethora of image fusion algorithms available. These methods are divided into three levels, which include pixel-level, feature-level, and decision-level [1]; most of these fusion methods belong to the pixel-level paradigm. However, they have the handicap that they make impossible to represent the whole visual information contained in a set of images as a single fused image, without losing information [2]. In [3], other disadvantages of pixel-level fusion strategies are mentioned, as they do not consider the spectral, spatial, and radiometric characteristics; they need higher matching accuracy. When matching accuracy is low, skewbald appears easily in object boundaries and shade region.

On the other hand, the feature-level methodology requires the extraction of features from the source data (e.g. segmentation). One of the main problems posed by this kind of methodology is the high dependence on the strategies used to extract features regarding the resulting fused image. Finally, the fusion algorithm based on decision-level, uses as input data the feature extraction and classification of the source images. When using this kind of strategy, a major problem is posed: the need of working with data at a semantic level, so as to define rules with a particular meaning in the context where they are being used (ontology). In agricultural water management, a large amount of spatially distributed data is avail- able, such as vegetation index maps, cover texture maps, crop evapotranspiration maps, leaf area index (LAI) maps, soil moisture maps and soil conductivity maps, among others. For this reason, it is necessary to develop strategies for integrating this large amount of data into a smaller volume structure, where these integrated data become appropriate information for the purposes previously stated. In this way, the goal of this work is to propose a methodology for object-based data fusion, which may be useful as a tool for agricultural water management. Specifically, a data fusion methodology is proposed considering a decision-level strategy, where the integration of spatially distributed data is possible. For this case study, these data correspond to a NDVI map and to a Lacunarity one [4], [5].

2. Materials and methods

2.1. Methodology

As mentioned above, the methodology proposed in this work can be classified as a decision-level strategy. The methodology proposes the integration of important data to water management at farm-holding scale. Also, this proposal is a general approach. This means it can be applied to multiple and different types of data defined by the user, in order to correctly characterize the phenomenon being studied. Its only restriction is that data must be spatially distributed (2D) (e.g. images, maps, spatially distributed in situ measurements, among others).

Fig. 1 shows a general diagram of the methodology proposed. Five essential stages can be identified. The first stage is the segmentation of the input 2D data. The algorithm used for this task consists of a clustering from the multi-modal gray level histogram [6]. In order to avoid over segmentation, a smoothing methodology based on the Wavelet Transform has been proposed [7]. Then, a larger number of clusters will be available for the original histogram than for higher degradation levels, due to a larger number of modes. This approach gives a multi-scale character to the segmentation process and, consequently, to the data fusion process.

In the second stage, objects extraction and labeling, the objects obtained in the previous stage must be identified. In the third stage, a feature extraction of the objects obtained in the labeling process must be carried out. It is important to notice that the results that may be obtained through this methodology are strongly related to the type of feature or attribute indicator being used. If it is a NDVI map, for example, the NDVI mean value could be a representative feature for the object under analysis. The mode value could be another representative feature. It is also possible to use morphological features or, at a higher level, a semantic interpretation of features. The number and type of feature indicators will strictly depend on the ones that better represent the phenomenon to be studied. Then, at a later stage, a joint matrix must be generated, which integrates every object obtained for the different inputs.

The fourth stage consists of a clustering process of the matrix previously obtained. For this purpose, in this work the Ward's Hierarchical Clustering method has been used, through the Euclidean norm as metric. Finally, these clusters are used as training data to create decision trees. In general, these rules have a semantic character, as they have a specific meaning in the context being analyzed (for the study case, agriculture water management). Then, it is possible to input the total 2D data that were used, for their re-evaluation and subsequent generation of fused data.

2.2. Data set

The data used in this work were collected through a Quickbird image, which was acquired on February 18^{th}, 2005, in Peumo Valley, O'Higgins Region, Chile (34°18'6''S; 71°19'11''O). The scene used has an area of 9.43 hectares and corresponds to 512 × 512 pixels in the panchromatic image. Fig. 2(a) shows a color composition (Near Infrared- Green-Blue) of the multispectral scene that has been used for the application of the methodology proposed by this work. Fig. 2(b), shows its corresponding panchromatic image.

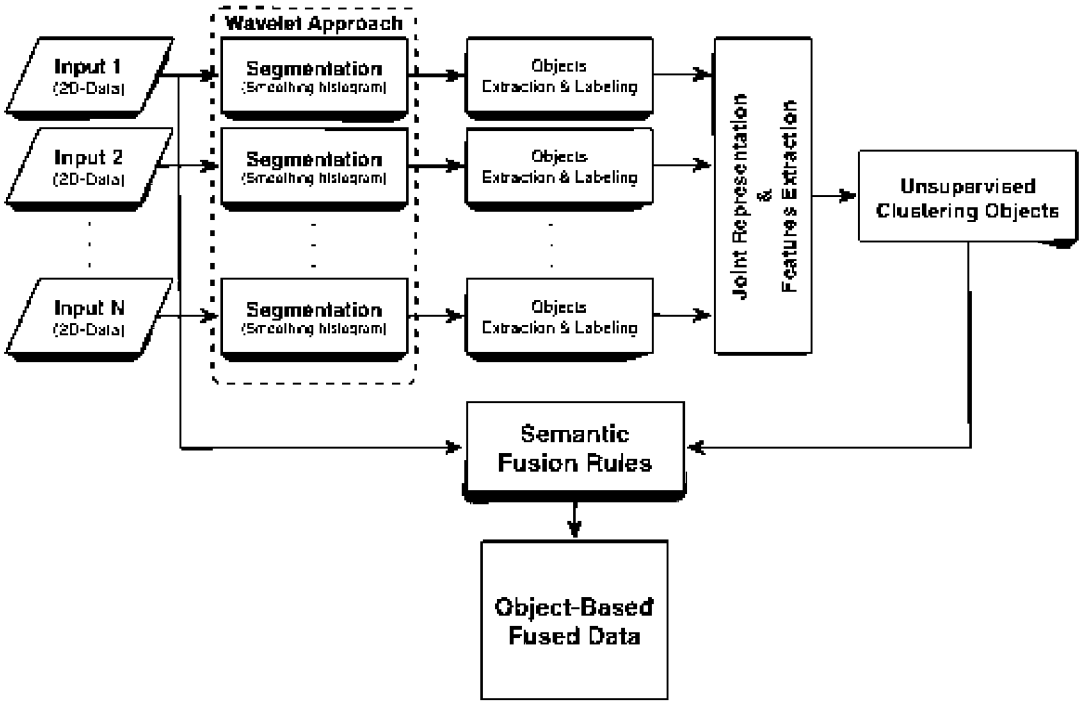
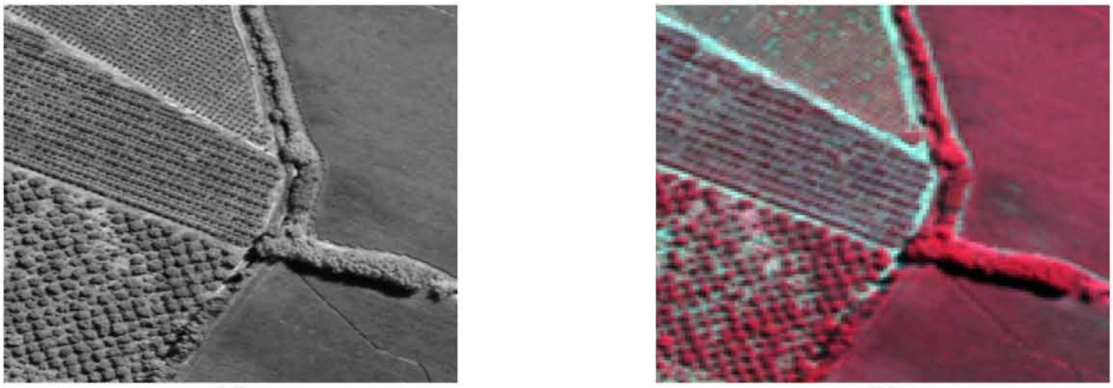


Figure 1: General methodology

3. Results

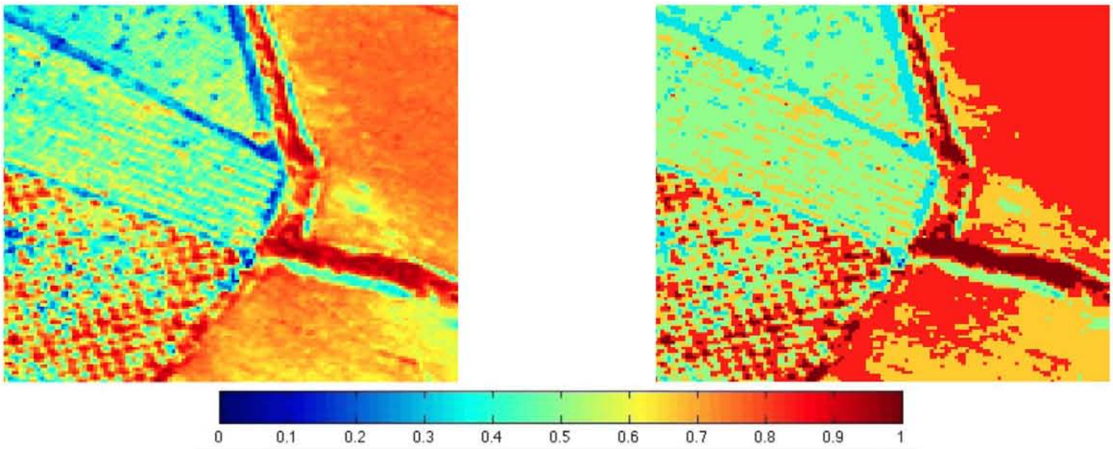
The methodology proposed in the previous section was applied to 2 sets of data (Input N = 2, see Fig. 1). The first one corresponds to a NDVI map (Fig. 3a) of the study area and the second one corresponds to a Lacunarity map (Fig. 4a) obtained by means of the algorithm proposed in [5]; where Lacunarity is a measure of how data fills space. It complements the fractal dimension, which measures how much space is filled. This map was estimated for a gliding box, of $\omega_{size} = 15$. The segmentation process was applied to the original histogram of the Lacunarity data and to the second level of the Wavelet degradation for the NDVI map. Taking this segmentation, at the object extraction and labeling stage, 41 objects were obtained for the Lacunarity map and 7 were obtained for the NDVI one (Fig. 4b). For each case, these objects met a homogeneity criterion, from the point of view of the values that form the objects.

Previous to the feature extraction stage, it was necessary to generate an association between the objects of both data maps. This process aims to obtain new objects that, at the same time, meet a homogeneity criterion both for NDVI and Lacunarity. However, it is valid to notice that the criterion or criteria used to generate this joint representation of the input data will depend on its/their features and on the type of final data intended to be obtained. In this study case, a logical operator “and” was applied; a total of 121 homogeneous objects were obtained, both in NDVI and Lacunarity values. At this stage of the process, the 2D input data (Lacunarity and NDVI maps) were transformed into two data structures (1D) with 121 elements. All the original values that compose each object were stored in different positions of the structure. A representative feature was defined for each of the 121 objects. Specifically, the mean value of each object belonging to Lacunarity and NDVI vector has been used. At the end of this process, a 2×121 vector was obtained, where dimension 2 is given by the Lacunarity and NDVI vector and dimension 121, by the total number of homogeneous objects.



(a) (b)

Figure2: (a) Panchromatic and (b) Multispectral image of Quickbird scenes on February18th, 2005, in Peumo Valley, O'Higgins Region, Chile



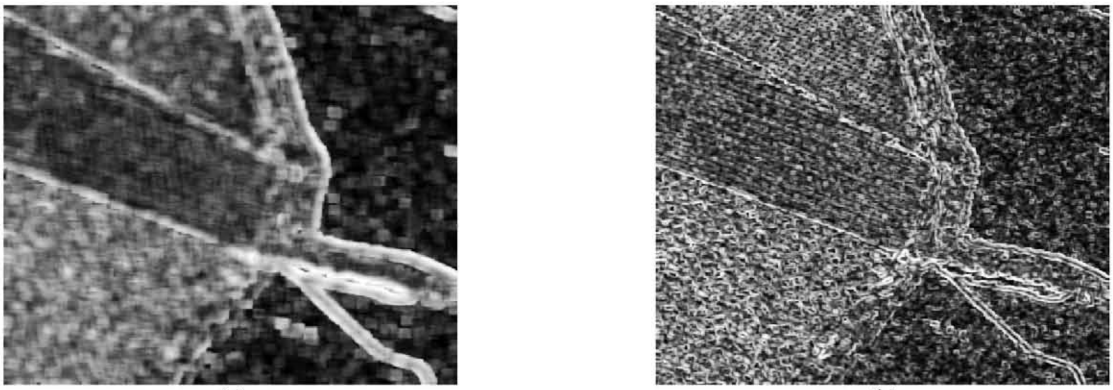
(a) (b)

Figure 3: (a) Original NDVI and (b) Thresholding NDVI of the study site

At the unsupervised clustering object stage, the Ward's Hierarchical Clustering method was used. The cluster number was set to equal the number of objects obtained from the NDVI smoothing segmentation (7). Finally, the previous result was used as a training cluster for the decision tree that delivered a total of 4 types of homogeneous covers regarding both vegetation vigor and vegetation texture. The dichotomy rules of this decision tree correspond to the Semantic Fusion Rules (SFR) for integrating the NDVI and Lacunarity data:

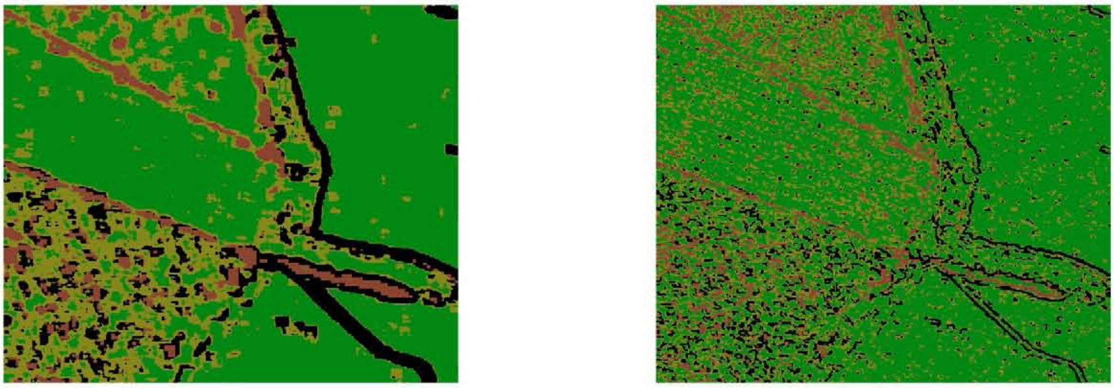
1. *if Lacunarity< 16.67 then node 2 else node 3*
2. *if Lacunarity< 10.23 then node 4 else node 5*
3. *if NDVI< 0.456 then node 6 else node 7*
4. *Type-cover 4*
5. *Type-cover 2*
6. *Type-cover 1*
7. *Type-cover 3*

These rules were applied to the 2D input data, NDVI and Lacunarity with ω_{size} =15 (Figs. 3a and 4a), having the fused image shown in Fig. 5(a) as a result. In this figure, it is possible to see some very homogeneous areas, with a high vegetation vigor, like the ones labeled "Type-cover 4" (Green) and other areas with a low vigor and affected by a high variability in their texture, labeled



(a) (b)

Figure 4: Two scale of Lacunarity map using: (a) $\omega_{size} = 15$ and (b) $\omega_{size} = 7$



(a) (b)

Figure 5: Object-based fused information of the NDVI and Lacunarity maps using SFR, with: (a) $\omega_{size} = 15$ and (b) $\omega_{size} = 7$

"Type-cover 1 (Siene), 2 (Yellow) and 3 (Black)". The same rules were also applied to the same NDVI map, but the Lacunarity map with $\omega_{size} = 7$ (Fig. 4b) was used as the texture map. This map captures texture details at a lower scale, but with harder transitions, unlike the map estimated with $\omega_{size} = 15$, which has smoother transitions. The results can be seen in Fig. 5(b), where it is possible to see that the areas that were generated as homogeneous ones, both in NDVI and Lacunarity, have a lower volume and a better spatial characterization. This evidences the potential of the Lacunarity algorithm as a tool for a multi-scale analysis of the area under study.

4. Conclusions

This work has proposed a new methodology for object-based data fusion, with a multi- scale character. This potential, is mainly given by the smoothing process of input data histograms, what makes a controlled segmentation possible. It is possible to reduce the volume of input data. In this particular case, it reduces two 2D data structures (NDVI and Lacunarity) to a single map with information which characterizes, in a summarized way, the different details of each cover at the scene under study. Finally, this way of representing data has generated semantic fusion rules (SFR) through object-based analysis of the different input data.

Study results should be related to relevant literature. Possible sources of error should also be discussed. Recommendations for future research should be made.

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