Remote Sensing Imagery for Soil Characterization: a Wavelet Neural Data Fusion Approach

VINCENTO BARRILE (*), GIUSEPPE ARMOCIDA (*), GIULIANA BILOTTA (**)
* Department DIMET - Faculty of Engineering
Mediterranean University of Reggio Calabria
Via Graziella Feo di Vito 89100 Reggio Calabria, Tel +39 0965 875301
ITALY
** Department of Planning - PhD NT&ITA -
University IUAV of Venice
Santa Croce 191, Tolentini 30135 Venice
ITALY
vincenzo.barrile@unirc.it armocida.g@libero.it giulianabilotta@libero.it

Abstract: - Technological advances in remote sensing imagery allows to obtain high resolution images, helpful in soil characterizing, monitoring and predicting natural hazards. On the other hand, the different kind of in-service sensors allows inferences on a large frequency band. In spite of this, due to the increasing requirements of industrial and civil entities, the academic research is actually involved in improving the quality of imageries. The aim is to implement automatic tools able to work in real-time applications, above all in order to solve pattern identification problem in remote sensing. Within this framework, our work proposes a data fusion methodology, based on the Multiscale Kalman Filter, in order to improve soil characterization in Synthetic Aperture Radar surveys.

Key-Words: Data fusion - Neural Networks - Multiscale Kalman Filter – Pattern recognition

1 Introduction
Remote sensing imageries are nowadays very useful in many scientific, civil and military frameworks. A special interest involves the land monitoring in order to improve and make better soil exploitation and land usage. That's why an automatic system able to identify the ground composition could be very useful for civil defence authorities as well as for economic and industrial aims. A valid help can be brought just by remote sensing, since images captured by airborne or satellite can be very descriptive of a relatively large geographical area or, on the contrary, can provide useful information of a restricted zone with very good resolutions, according to the exploited sensors. In this context, the cheapest information can be provided by images obtained from satellites operating into the visual or infrared spectra, but they do not allow to make such inferences above described. This kind of problem, in fact, can be considered as an inverse problem of pattern recognition, which has a definite place in remote sensing, particularly because of its effectiveness in geospatial analysis (see [1] and references within). This kind of problem, in fact, can be considered as an inverse problem of pattern recognition, which has a definite place in remote sensing, particularly because of its effectiveness in geospatial analysis (see [1] and references within). Moreover, it can be definitely defined as an ill-posed problem, since different kind of soils/areas can response in the same way within the visual frequency range of the electromagnetic spectrum.
A correct solution of pattern recognition problems in remote sensing could be very useful in such frameworks as urban growth of developing countries: here, suburbs are usually composed by unauthorized buildings often constructed without considering the real characteristics of the territory. Moreover, a correct soil classification could improve the agricultural activities. Usually, traditional pixel or object based classification techniques have more difficulties to deal with classes automatically extracted from very high resolution images. On the contrary, a solution can be approached by a joint use of RGB and infrared images in a sort of data fusion methodology, and exploiting Soft Computing techniques such as Neural Networks to well-pose the problem of land characterization. The new advances in Soft Computing, in fact, make these techniques very reliable for such applications, with the advantage of implementing a real-time classifier able to detect peculiar characteristics of a particular area (please, see [2], [3] and references within).

Our proposed approach started from IKONOS images and is divided in two steps: the first one is based on a data fusion approach in order to obtain an image having a higher resolution than the starting images. The latter step is the proper classification procedure, starting from the data fusion’s useful output. Thus, A Multiscale Kalman Filter (MKF) has been applied to fuse red, green, blue and near-infrared images. Subsequently, peculiar numerical quantities able to discriminate the various kinds of soil have been extracted from the obtained quality-increased image by means of the Wavelet Transform (WT) [4, 5]. Finally, a Multi-Layer Perceptron Artificial Neural Network (MLPANN) [6, 7, 8] has been suitably trained and tested in order to automatically detect each kind of area. During the whole procedure, great care has been paid to reduce as much as possible the number of selected...
features used as MLPANN inputs, in order to overcome the classical problem of "curse of dimensionality", i.e. the increase of system complexity without remarkable advantages in terms of classification performances, due to an excessive number of training inputs. In this way, a fast and robust system can be implemented for a real-time help to the authorities in land monitoring.

2 The data fusion approach for image quality enhancing
Data fusion [9, 10, 11] can be defined as the synergistic use of knowledge from different sources to assist in the overall understanding of a phenomenon: data fusion algorithms can be broadly classified as either phenomenological or non-phenomenological. Phenomenological algorithms utilize a knowledge of the underlying physical processes as a basis for deriving the procedure for fusing data. Non-phenomenological approaches, in contrast, tend to ignore the physical process and attempt to fuse information using the statistics associated with individual segments of data. Research on the subject of data fusion aims to obtain more comprehensive information about the system analyzed by using the strategy of combining information from multiple sensors. Particularly for the image sensor, the recent advances in this field make possible to combine information across the electromagnetic spectrum by the fusion of multi-modal images, i.e. by the so called image fusion. The general procedure for image fusion is depicted in Fig.1 [12].

Fig.1: Block schema of the general image fusion procedure

A lot of different algorithms exploiting well known image fusion techniques are available in scientific literature (see Error! Bookmark not defined. and references within). The most known image fusion algorithms are based on Optimal Filtering (OF), Multi-Resolution Analysis (MRA), Bayesian inference, Dempster-Shafer Theory (DST), or even heuristic methods such as Artificial Neural Networks (ANN). Here, we introduce an innovative data fusion algorithms, i.e. the exploited MKF.

3 The MKF algorithm: how to merge multiple images at different scales
The MKF technique belongs to the realm of multisresolution stochastic processes [13, 14], where one-dimensional time series or multidimensional images have a time-like variable, commonly referred to as scale. Therefore, the MKF algorithm merges data at different resolution scales. Loosely speaking, an image (2D signal) can be decomposed from the coarse to the fine resolution. At the coarsest resolution, the signal will consist of a single value. At the next resolution, there are $m=4$ values, and, in general, at the $m$-th resolution, we obtain $q^m$ values. The values of the multiscale representation can be described on the index set $(m,i,j)$, where $m$ represents the resolution and $(i,j)$ the location index. The scale-to-scale decomposition can be schematically depicted as a tree structure. Resuming, the estimation of the state (i.e., the image at the different merging resolution) by the MKF proceeds along the following steps: (1) initialization, corresponding to the finest scale node; (2) upward step, used to estimate the state and the error co-variance matrices by combining the available measurements and the predicted values (for each node we obtain $q$ predictions from each of the $q$ child nodes; they are subsequently merged to obtain a single prediction); (3) downward step, in which the information is propagated downward after the upward step is completed; the estimation at a particular node in the downward step is equal to the sum of its estimate in the upward step and the difference in the estimations of the parent node in the downward and upward step weighted by a suitable coefficient.

4 Experimentations
As described within the introduction, our experimentation has been based on IKONOS images taken on Bagnara Calabra (Calabria region, province of Reggio Calabria, into the South Italy, LON 15° 49’ 0'' E, LAT 38° 17’ 0” N). The considered channels for the MKF are the following: red, green, blue and near-infrared channels. Characteristics of surveys are resumed into Table 1. Original images have a resolution of 1991x1979 pixels; they have been cut considering the area (508,5)x(1991,1206): in this way, the considered images have a resolution of 1483x1201 pixels. Fig.2 draws the sources at the different bands.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Bits/ Pixel</th>
<th>Datum</th>
<th>Projection</th>
<th>Resolution</th>
<th>Dimensions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panchromatic</td>
<td>11</td>
<td>WGS84</td>
<td>UTM 33</td>
<td>1 m</td>
<td>7964x7916 pixel</td>
</tr>
<tr>
<td>Red, Green, Blue, NIR</td>
<td>11</td>
<td>WGS84</td>
<td>UTM 33</td>
<td>4 m</td>
<td>1991x1979 pixel</td>
</tr>
</tbody>
</table>

Table 1: Characteristics of IKONOS survey.
First of all, let us remark that the selected geographical area is highly affected by property speculation and unauthorized buildings. Thence, for instance, it is possible to detect urban areas even among cultivations. In this way, the ill-posedness of the problem is highly increased, as well as the difficulty of classification procedure. Therefore, traditional pattern recognition models are not advised to be used in such kind of applications. Complementarily, a suitable and highly reliable data fusion technique could be very useful in order to enhance the characteristics of the different areas (i.e. classes) and reduce such kind of noise as speckle noise.

These data are now considered as the input to the fusion algorithm: the MKF merges data at different resolution scales. The model of the MKF has been applied by using a self-implemented Matlab® function, and results of the image fusion process are described by Fig.3.

Subsequently we use the full resolution image, i.e. the fused image at m=4 resolution level for our experimentations. In this image we can distinguish four different areas: urban, mountain, sea and cultivation areas. A comparison between the fused data and the result of the superimposition of red, green and blue channels of the IKONOS survey can be carried out by computing the standard deviations of different samples related to these areas. Three samples for each areas are resumed by Tab.2.

**Fig.2:** The IKONOS sources, i.e. the survey on the selected geographic site (Bagnara Calabra), split into the four working-channels: red (top-left), blue (top-right), green (bottom-left) and near-infrared (bottom-right).

**Fig.3:** MKF's at the different merging resolution.
The values of the standard deviation (STD) and the Squared Mahalanobis Distance (SMD) [15, 16] for the grey scaled version of the superimposed RGB image and for the fused image at resolution m=4, have been indicated in Tables 3-4. We can note that each sample in the fused image has a standard deviation lower than the corresponding sample of the input image. Therefore, in the fused image at full resolution, neighbour pixels corresponding to the same area, have an intensity level more similar and this fact means that the fusion process has been able to reduce the negative effects of the speckle noise.

On the other hand, SMDs have been calculated as the distance between the four clusters representing the four classes (i.e. areas) and composed by the three corresponding selected samples (i.e. boxplots). In this way, it is possible to give an information about the quality of the data fusion procedure: the bigger the distance between clusters, the easier the subsequent procedure of classification.

Generally, the distances between clusters have been increased by using the MKF based data fusion approach, but in three cases, i.e. SMD$_{ua,ma}$, SMD$_{ua,ca}$ and SMD$_{ma,ca}$, they are still too small. It means a possible misclassification by using classical techniques of pattern recognitions. Therefore, it is strictly important to implement an expert system, able to identify as good as possible the different classes, starting from measurements enhanced by the data fusion approach.

<table>
<thead>
<tr>
<th>Image merged by MKF at m=4</th>
<th>Gray scaled RGB superimposed image</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMD$_{ua,ma}$ (between urban and mountain areas)</td>
<td>0.9</td>
</tr>
<tr>
<td>SMD$_{ua,sa}$ (between urban and sea areas)</td>
<td>6.04</td>
</tr>
<tr>
<td>SMD$_{ua,ca}$ (between urban and cultivation areas)</td>
<td>0.67</td>
</tr>
<tr>
<td>SMD$_{ma,sa}$ (between mountain and sea areas)</td>
<td>10.22</td>
</tr>
<tr>
<td>SMD$_{ma,ca}$ (between mountain and cultivation areas)</td>
<td>0.52</td>
</tr>
<tr>
<td>SMD$_{sa,ca}$ (between sea and cultivation areas)</td>
<td>23.83</td>
</tr>
</tbody>
</table>

Table 4: Comparison of the MDs for samples taken by merged and superimposed images.

5 Classification of similar areas by WT and MLPANN

Subsequently, we implemented the database useful for training the MLPANN. For each above described sample (boxplot), we apply the following procedure: (1) within the i-th boxplot we considered a 8x8 sliding window; (2) within the selected window, we apply the Daubechies 1 bidimensional WT, with a third-level multiresolution analysis; (3) we collected the wavelet approximation coefficients at level 1, 2 and 3 as features; (4) finally we moved the sliding window of 4 pixel in horizontal as well as in vertical sense inner the same boxplot. In this way, we collected 21 features and 2700 patterns useful to train a suitable MLPANN. The training procedure has been carried out by using the Levenberg-Marquardt regularization [17], and considering a neural network with two hidden layer, having 10 and 6 neurons respectively (only the log-sigmoid was used as activation function). Subsequently, the highest-resolution image obtained by MKF data fusion as well as the grey scaled RGB superimposed image have been classified by the implemented MLPANN, by colouring areas according to their classification, with the following coding: white colour if the area is classified as sea; black colour if the area is classified as mountain; dark-grey colour if the area is classified as urban; light-grey colour if the area is classified as cultivation.

<table>
<thead>
<tr>
<th>Image merged by MKF at m=4</th>
<th>Gray scaled RGB superimposed image</th>
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</thead>
<tbody>
<tr>
<td>66.76</td>
<td>84.26</td>
</tr>
<tr>
<td>60.61</td>
<td>76.51</td>
</tr>
<tr>
<td>65.53</td>
<td>75.88</td>
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<tr>
<td>27.02</td>
<td>27.32</td>
</tr>
<tr>
<td>23.46</td>
<td>24.85</td>
</tr>
<tr>
<td>16.89</td>
<td>19.28</td>
</tr>
<tr>
<td>2.49</td>
<td>4.10</td>
</tr>
<tr>
<td>2.57</td>
<td>4.27</td>
</tr>
<tr>
<td>2.44</td>
<td>3.60</td>
</tr>
<tr>
<td>10.90</td>
<td>18.14</td>
</tr>
<tr>
<td>6.36</td>
<td>9.24</td>
</tr>
</tbody>
</table>

Table 3: Comparison of the STDs for samples taken by merged and superimposed images.
is classified as cultivation. Fig.4 shows results of classifications.

![MKF's merged image at resolution m=4](image1)

![Gray scaled version of the RGB superimposed image](image2)

**Fig.4: Results of pattern classification.**

### 6 Discussion about results and conclusions

Obtained results are very encouraging, as it is shown by quantitative results resumed into the Table 5.

<table>
<thead>
<tr>
<th></th>
<th>Image merged by MKF at m=4</th>
<th>Gray scaled RGB superimposed image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy</td>
<td>88.45%</td>
<td>72.67%</td>
</tr>
<tr>
<td>Computational time</td>
<td>42 s</td>
<td>38.2 s</td>
</tr>
</tbody>
</table>

**Table 5: Quantitative evaluation of obtained results: cross-comparison of overall accuracy and computational times for both MKF’s merged and RGB superimposed images.**

The overall accuracy has been increased of, more or less, 23%, whereas the calculation elapsed time has been increased of, more or less, 10%. Let us remark how it is an interesting results, since the geographical area selected for the application of the proposed method is highly affected by property speculation and unauthorized buildings. The classification carried out by MLPANN by exploiting the wavelet approximation coefficients appears better in the case of MKF’s merged image than for the grey scaled RGB superimposed image. Let us remark how, on the contrary, classical pixel or object based classification techniques have more difficulties to deal with classes extracted from such kind of images like those we can by using sensors working into the visible spectrum.

Moreover, the usage of the MKF allows to have neighbourhood pixels, corresponding to the same area, with an intensity level more similar, i.e. a significant reduction of the negative effects of the speckle noise. The usage of WT for feature extraction, on the other hand, gives us useful informative content of the inspected image by means of a restricted number of elements (i.e. wavelet approximation coefficient, containing the most percentage of information), so reducing the problem of "curse of dimensionality" in training the MLPANN. Let us denote how our proposed algorithm suffers of some mistakes next to areas in which such objects as clouds or cloud-shadows are present, or when the different classes are very mixed each other. Nevertheless, all considering, our work can be positively considered within the framework of solving inverse pattern recognition problems into the remote sensing imagery.

**References:**


