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A comparison between a traditional and a geometrical supervised classifier to produce land cover Maps from SPOT5 images

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Abstract. The new high-resolution images from the satellites as IKONOS, SPOT5, Quickbird2 give us the opportunity to map ground features, which were not detectable in the past, by using medium resolution remote sensed data (LANDSAT). More accurate and reliable maps of land cover can then be produced. However, classification procedure with these images is more complex than with the medium resolution remote sensing data for two main reasons: firstly, because of their exiguous number of spectral bands, secondly, owing to high spatial resolution, the assumption of pixel independence does not generally hold. It is then necessary to use new spectral classifiers taking into account also proximal information. In this view, it is necessary to combine both "spectral" and "spatial" features to optimise land use classification. Standard supervised classification techniques, so-called "per-pixel" classifiers, use only spectral information of remote sensing image, whereas neglecting the relationships between neighbouring pixels. The objective of this work is the comparison between a conventional supervised classifier, as "Maximum Likelihood" algorithm, and a spatial classifier based on a searching algorithm of a given geometrical pattern.

The data in this study were a remote sensing image taken by SPOT5 satellite in July 2007 and used to discriminate the water melon cover class. Applying the object recognition tecnique the overall accuracy increased of about 12%.

Keywords: High resolution satellite images – Maximum Likelihood – Object-oriented.

Comparaison entre classificateurs traditionel et géométrique pour la production de cartes de couverture du sol à partir d'images SPOT5

Résumé. *Les nouvelles images à haute résolution des satellites comme IKONOS, SPOT5, Quickbird2 nous donnent la possibilité de dresser des cartes caractéristiques du terrain, qu'on ne pouvait pas relever, par la télédétection d'images de moyenne résolution (LANDSAT). Des cartes plus précises et fiables, de couverture du sol peuvent alors être produites. Toutefois, la procédure de classement de ces images est plus complexe que la classement des données de télédétection à résolution moyenne pour deux raisons principales: tout d'abord, en raison de leur nombre exigu de bandes spectrales, d'autre part, en raison de la haute résolution spatiale, l'hypothèse de l'indépendance de pixels ne peut plus être acceptée. Il est alors nécessaire de recourir à de nouveaux classements spectraux en tenant compte également de l'information proximale. De ce point de vue, il est nécessaire de combiner l'information «spectrale» et «spatiale» afin d'optimiser la classification des sols. Les techniques de classification supervisée standard, soi-disant «per-pixel», utilisent uniquement l'information spectrale de la télédétection image, négligeant les relations entre les pixels voisins. L'objectif de ce travail est la comparaison entre un classificateur conventionel supervisé, en tant que «Maximum Likelihood» algorithme, et un classificateur spatial sur la base d'un algorithme de recherche d'un modèle géométrique. Les données de cette étude sont une image de télédétection par satellite SPOT5 prise en Juillet 2007 et utilisée pour l'individuation des champs de pastèque pour identifier sa classe de couverture. L'application de la technique de «object-recognition» a augmenté la précision globale du classement d'environ 12%.*

Mots-clés. *Haute résolution des images satellite – Maximum Likelihood – Object-oriented.*

I – Introduction

Traditional methods of remote sensing analysis, as aerial-photo interpretation, have taken advantage from the overlapping of adjacent photographs to assess size and structure. This method has produced successful results, but it has also been problematic and expensive for various reasons; for example, the acquisition of aerial photographs may be difficult, owing to the bad weather conditions. Since at present there is a number of high resolution satellites in orbit, acquisition of satellite imagery is now much easier and more readily available than photography. Moreover, once aerial photographs are obtained, interpretation must be made on individual photographs, often numbering in hundreds or thousands.

In early 2002, two new high resolution satellites were launched, bringing to three the total number of satellite sensors capable of delivering imagery with resolution under 5 meters. These satellites will continue to proliferate and, as a new satellite is added, the price of this type of imagery will continue to drop. Moreover, some of these new satellites have larger footprints (cover larger areas) without any loss of spatial resolution. Although features can always be extracted from high resolution imagery through visual means with hand delineation procedures (Lillesand *et al.*, 2004), this approach is very time consuming and subjected to human error. As high resolution imagery is collected in digital format and is multispectral, this makes it a good candidate for an automated approach of feature extraction. To date the standard automated mapping approach has been to use unsupervised or supervised classification techniques. Higher spatial resolution improves the ability to differentiate features, but, in complex environments, different classes can have identical spectral reflectance and, reversely, the same class can have different spectral reflectance values. To improve classifications, size, shape, texture, context, and pattern can be incorporated into classification methods. New algorithms, such as nearest neighbour analysis, neural networks, decision trees and the mixing of spectral and textural data, can be applied (Donnay *et al.*, 2001, Herold *et al.*, 2003).

This improves the results, but further increases the skill level required for use (Herold *et al.*, 2003).

Object-oriented approaches classify objects rather than individual pixels (Geneletti and Gorte 2003). The traditional methods rely entirely upon the spectral information in an image, while neglecting the spatial arrangement of the pixels. Pixel-based classification methods frequently group dissimilar pixels with the larger, surrounding class. The Feature Analyst approach to object-recognition and feature extraction overcomes these shortcomings by using inductive learning algorithms and techniques to model the feature-recognition process. The user gives the system a sample of extracted features from the image and the system then automatically develops a model that correlates known data (such as spectral or spatial signatures) with targeted outputs (i.e., the features or objects of interest). The learned model then automatically classifies and extracts the remaining targets or objects. This approach leverages the natural ability of humans to recognize objects in complex scenes.

Object-oriented classification allows relevant objects to be of any size. Object-oriented classification is not without drawbacks. Classifications are difficult in areas, where complex obstacles and shadows may lead to misclassification. Moreover, advanced user expertise in processing techniques is frequently needed to develop classification algorithms (Mitri *et al.*, 2004).

II – Methodology

Maximum Likelihood algorithm is a conventional statistical classification technique that allocates each pixel of an image to the class with which it has the highest likelihood or 'a posterior' probability of membership. Let the spectral classes for an image be represented by the categorical variable ω_i, i=1,…..,M with M mutually exclusive categories and let $\mathbf{X}=\mathbf{X}(\mathbf{u}_\alpha)$ be B-variate random vectors

(B = number of spectral bands of the image), the pattern observations describing a point at the position **u** $_\alpha$.

In remote sensing the measurement vector **X,** referred to the pixel of spatial coordinates **u**$_\alpha$ (α=1,….,n), is a column of brightness values for the image and the training data for ground cover type are associated to the sample points **u**$_\alpha$.

To determine the class or category (Duda, 1973) to which a generic pixel vector **X**(**u)** belongs, it is strictly the conditional probabilities:

$P(\omega_i \,|\, \boldsymbol{X}(\boldsymbol{u}))$ i =1,……..,M

that are of interest. This probability gives the likelihood that the class ω_i prevails for the pixel at the position **u.**

Maximum Likelihood algorithm assigns each pixel to the class whose 'a posterior' probability is maximised:

assign the position ***u*** *at the class* ω_i ☐ $P(\omega_i \,|\, \boldsymbol{X}(\boldsymbol{u})) = \max_\omega P(\omega \,|\, \boldsymbol{X}(\boldsymbol{u}))$

$P(\omega_{i|}\, \boldsymbol{X}(\boldsymbol{u}))$ are unknown, but suppose we have sufficient training data for each class that can be used to estimate a "spectral" probability density function $P(X(u)\,|\,\omega_i)$ for a cover type, i.e. the chance of finding a pixel from class ω_i , say, at the position **X**(**u).** $P(\omega_{i|}\, \boldsymbol{X}(\boldsymbol{u}))$ is then obtained by applying the Bayes rule:

$$P(\omega_i \,|\, \mathbf{X}(\mathbf{u})) = \frac{P(\mathbf{X}(\mathbf{u})|\omega_i)P(\omega_i)}{P(\mathbf{X}(\mathbf{u}))}$$

where $P(\omega_i| \boldsymbol{X}(\boldsymbol{u}))$ represents the posterior probability of a pixel with data vector **X**(**u)** to belong to class i, $P(\boldsymbol{X}(\boldsymbol{u}))$ is the unconditional probability that the pixel **u** occurs in the image, $P(\omega_i)$ is the 'a priori' probability of the class ω_i. It is assumed that spectral probability density function is of the form of multivariate normal model.

Feature Analyst uses an inductive learning based approach to object-recognition and feature extraction. The Feature Analyst workflow (VLS, 2004) includes the following steps:

1. User digitalizes several examples of the feature to collect (training data set). Feature Analyst is an approach similar to traditional supervised classifier, because the user needs to supply ground truth sites of each feature of interest. However, the main difference is that it uses these sites to find areas in the image that are similar, not only on the basis of spectral signature but also of geometrical shape parameters. Typically, to start only a few examples are required.

2. User selects the feature type, which automatically sets all of the learning parameters behind the scene. The contextual classifier can be adjusted based on the feature to be extracted. It is possible to define the spatial context for the feature of interest and it is important to use an input pattern that captures the essence of the feature you are trying to extract. In our case study the geometrical pattern applied is represented in figure 1 because it would work well for extracting land cover features on 10 meter imagery (VLS, 2004). The input representation describes the pattern of pixels considered around a target pixel to classify it.

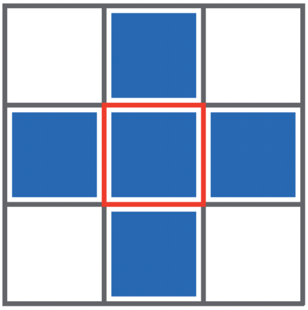


Figure 1. Pattern recognition in supervised classification of water melon field.

The key is to use an input representation that captures the essential spatial structure of the feature of interest. In general, the more complex the pattern is (this relates also to image resolution) the more input pixels are required.

The algorithm was used by the following supplementary settings:

- the imagery had four available bands and all of them were used;
- objects with less than 5 pixels were automatically aggregated with the most appropriate neighbouring object;
- rotated instances were included so that classification of similar objects oriented differently was allowed.

3. User extracts feature.

4. Results analysis and, if required, the user provides “positive” and “negative” examples to remove clutter and improve classification. This tool allows the user to define new examples of “correct,” “incorrect,” and “missed” areas so to produce a new output more refined than the previous one. This process can be repeated as many times as necessary. Clutter is the most common form of error in feature extraction. The objective of clutter mitigation is to remove false positives. Thus, the learning task is to distinguish between false positives and correctly identified positives. The user generates a training set by labelling the positive features from the previous classification as either positive or false positive. The trained learner then classifies only the positive instances from the previous pass. The false positives from the previous pass are considered correct in clutter mitigation and are thus masked out.

The classification is improved in successive passes, where each new pass is designed to remove one form of error from the results of the previous pass.

III – The case study

The study site is located along the coast of the Ionian Sea (south Italy), in an area widely cropped with water-melon. An image, dated July 2007, from SPOT5, with a spatial resolution of ten meters and four bands in visible and near/medium infrared spectrum, has been used.

Firstly, a data set of ground truths was collected on the scene, that was, then, split into a training data set, to recognise pattern on the study area, and a test data set, to validate the land cover maps.

Two supervised classifiers were compared: standard “Maximum Likelihood” (ML) and Feature Analyst (FA), both implemented in ERDAS software, using the same training and validation data sets.

IV – Results and discussion

Figure 2 shows the SPOT5 image of the investigated scene obtained by relating the bands 3, 2, 1 to the red green and blue channel (RGB) respectively. The data set of ground truths was obtained through a visual inspection of the fields by an expert and was split into the training data set and the validation data set. The validation data, within the target cover class, were selected by randomly drawing a given proportion (0.3) of the overall class occurrence. The same data sets, training and validation, have been used to produce and validate the land cover maps, obtained by applying the two classification techniques: traditional ‘Maximum Likelihood’ and combined approach performed by Feature Analyst.

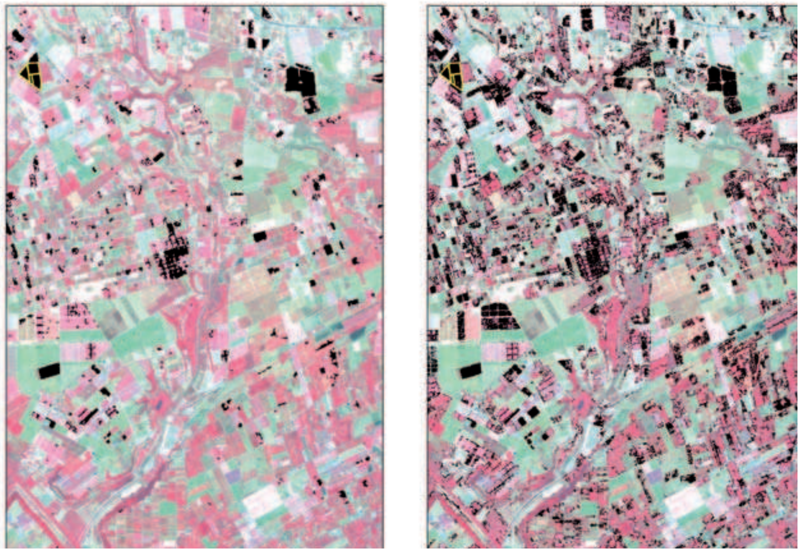
Figure 2. Image from SPOT5 satellite in combination of colours 321RGB.

Figure 3 and 4 show two sub-areas of the whole classified map that are of particular interest because including the two experimental farms (highlighted in yellow) in the AQUATER research project coordinated by CRA-SCA. In figures 3a and 3b there are shown the localizations of the water melon fields (black coloured), obtained by applying the object recognition tecnique and the traditional Maximum Likelihood classifier, respectively, overposed on the original SPOT5 image (fig.2). In the ML classifier the map was obtained by setting a probability threshold equal to 50% value, which allows to determine those pixels that are most likely to be incorrectly classified, so that they can be masked. However, ML has no possibility to improve classification by successive steps of a hierarchical feature extraction. The quality of the classification might be improved by applying a “majority” filter which substitutes the mode value within a moving window.

On the contrary in the FA only two post processing steps were necessary to improve classification, in order to distinguish between false positive and correctly identify positives on the basis of expert knowledge. For example, the area near the studied farm (highlighted with a blue circle in fig.4) used to orchard, was incorrectly identified as water melon also by FA at the first step. But after application of the “remove clutter” tool, it was correctly classified already at the second step. Using ML classifier it wasn’t possible to correct this error (even by applying the threshold), because this area has a spectral signature very similar to water melon.

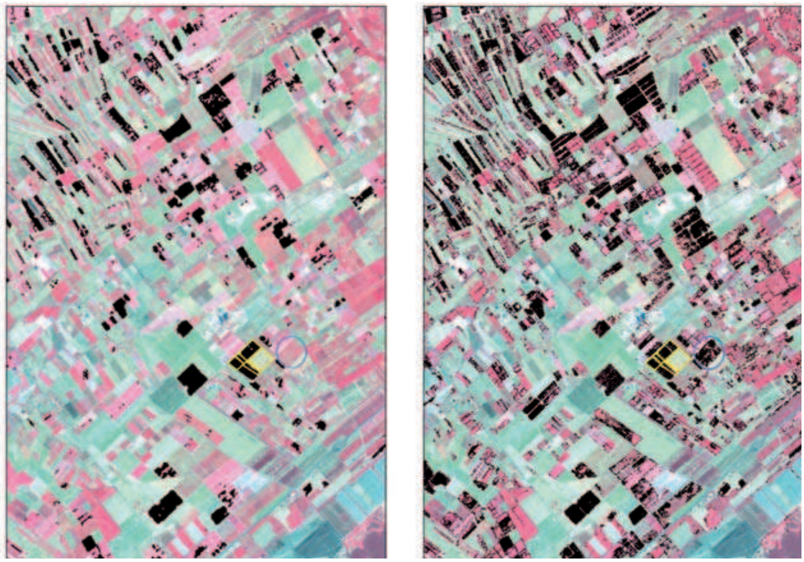
In order to compare the overall behaviour of the two classifiers, we calculated the overall accuracy obtaining 78% and 90% for ML and FA, respectively.

The better results in land cover class discrimination by FA were partly expected because FA approach utilises both (spectral and spatial) types of information. Differently, ML tecnique, using only spectral information per pixel, produces a map with several isolated and misclassified pixels and then a quite noisy land cover map. Therefore, the land discrimination by ML looks quite confused, whereas the FA classification map extracts more compact and homogeneous patterns corresponding to the fields cropped with water melon.



(a) (b)

Figure 3. Zoom details of the maps of water melon land cover (represented in black) obtained by applying the ERDAS Feature Analyst algorithm (a) and the traditional Maximum Likelihood classifier (b).



(a) (b)

Figure 4. Zoom details of the maps of water melon land cover (represented in black) obtained by applying the ERDAS Feature Analyst algorithm (a) and the traditional Maximum Likelihood classifier (b).

The ML map was deemed to overestimate the target class according to the judgement of an expert. The better performance of FA classifier compared with the ML one was evaluated not only on the basis of an objective statistical test, but also of the expert knowledge of the study area. This stresses the role of the expert knowledge in improving the classification by manually adding new polygons to initial training data set. However, this can also be assumed as a drawback of FA classifier, revealing the mostly heuristic character of the approach.

V – Conclusion

The resulting maps, obtained by applying the two classification methodologies, traditional Maximum Likelihood and object oriented tecnique, have been validated and the goodness of classification, evaluated by calculating overall accuracy, showed an increasing of 12%. The statistical comparison between the two approaches then shows Feature Analyst to be more accurate in water-melon pattern recognition, even if testing the method in more and different spatial contexts is needed, before declaring its better performance.

However, also other researchers, using object-oriented classification, have obtained similar results, such as Wang *et al.* (2004) that used IKONOS imagery to classify seven land cover types and obtained an overall accuracy of 89% for pixel level spectral classification and of 91% for spectral and object oriented classification.

The FA classifier has several advantages which proves it to be very promising in high resolution image classification. Those include:

- FA uses a spatial component of imagery which is the key when extracting features from high resolution imagery. In this way it is possible to extract more detailed vegetation information from high resolution imagery than what has been possible by using traditional classifiers working per pixel.

- The hierarchical learning of FA makes it easier to reach better results in classification, because it allows the user to select “correct”, “uncorrect” and “missed” areas in multiple steps.

Nevertheless, we think that the main drawback of this approach is the difficulty in defining the input pattern which captures most spatial structure of the feature being classified. This representation may be relatively easy for an isolated object, but may be more complex for a cropped field. Quite likely, there are other approaches, more efficient in homogeneous crop fields recognition, that integrate spatial and spectral information to classify high resolution imagery, such as the methodology that combines geostatistics with bayesian spectral approach (Goovaerts 2002, Fiorentino et al 2006).

Another disadvantage of FA relies on the ability of the user to introduce additional information into the initial training data set and then on the empirical nature of this approach.

To classify medium resolution imagery as Landsat TM, quite likely per pixel approach remains the better, whereas FA may perform better when we need more detailed information as individual plants and trees.

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