Annales Univ. Sci. Budapest., Sect. Comp. 30 (2009) 157-174

A FULLY SEGMENT-BASED METHOD FOR THE CLASSIFICATION OF SATELLITE IMAGES

I. László, B. Dezső, I. Fekete and T. Pröhle

(Budapest, Hungary)

Abstract. This paper presents a novel implementation of the *thematic classification of data obtained via remote sensing.* The identification of land cover categories on images is particularly important in the agricultural applications of remote sensing. In the analysis of satellite images, better results can be achieved if the similarity between the neighbouring pixels of land cover is utilized than in the case of pixel-based classification generally applied for digital images. To achieve this, one possible solution is the segment-based approach. The segment-based classification method introduced in the authors' previous article ([7]) has been improved. The possibility of joining the adjacent homogeneous image objects has been made more flexible. Furthermore, the whole procedure has consequently been made segment-based: the units of both clustering and class assignment have become segments instead of pixels. Besides, the human expert knowledge needed earlier at specific points of the classification has essentially been built into the program.

1. Introduction

Remote sensing (RS) has a continuously increasing role in survey, observation and control activities related to agriculture. In the past years, several monitoring tasks were supported by remote sensing in Hungary. Crop mapping and yield forecasting, flood, waterlog and drought monitoring, applications related to area-based agricultural subsidies and ragweed (ambrosia) control and exemption can be mentioned, among others. Remote sensing provides a sophisticated and cost-effective technology to monitoring activities, but the research and methodology that support the applications are also crucial points of the successful solution.

2. A brief overview of remote sensing

Earth observation satellites (e.g. Landsat and NOAA series) gather information from the Earth's surface. The reflected or emitted electromagnetic radiation is detected in several wavelength intervals and the result is stored in a *remotely sensed image*, a kind of digital image. A definite part of the whole electromagnetic spectrum, called optical band, has dominant importance in RS. The radiation leaving the surface is measured by sensors, each capturing a given subinterval of the spectrum. A multispectral image can be regarded as a matrix, the elements of which correspond to a given spot (approximately a square-shaped area) of the surface. The elements of image matrix, called *pixels*, are themselves vectors of the intensity values recorded by the different sensors.

RS images are categorized by five principal parameters. (1) *Pixel size* is the area of the surface spot belonging to one pixel, that is the elementary distinguishable area. Most images in our practice — the high resolution (HR) images — have a pixel size in the $25\,\mathrm{m} \times 25\,\mathrm{m}$ magnitude. (2) *Area coverage* is the size of the land piece covered by the whole image. (3) The available *spectral bands* and the respective wavelength intervals determine the possible thematic applications. (4) *Radiometric resolution* refers to the number of distinguishable intensity levels. The intensity values are usually the integer values of the interval 0–255 in the case of HR images. (5) *Period of acquisition* (e.g. 16 days) is the time between the passes of a given satellite over the same area.

Before starting the analysis of images, some *preprocessing steps* are carried out. Geometric and radiometric corrections transform the raw images into a uniform spatial and spectral system. The effects disturbing detection and data transfer can be decreased by atmospheric correction and noise filtering. In the case of several images, preprocessing steps make it possible to use them simultaneously in thematic mapping applications.

The ratio of reflected and incident radiation, the so-called *reflectance* heavily depends on the land cover and the wavelength. The *reflectance function* of a given land cover gives the reflectance along the (reflective) optical band. Every land cover category has its own characteristic reflectance function, which depends on the phenological phase and the maturity of vegetation. This fact can be used to make distinction between land covers, which is a fundamental requirement of RS. Figure 1 shows the reflectance function of a typical cultivated crop. Horizontal

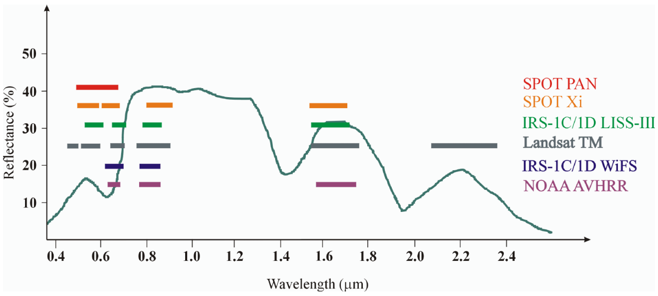


Figure 1. A typical reflectance function of vegetation and the bands of satellite sensors

lines in the figure show examples of the spectral bands covered by some sensors.

Practical applications of determining land covers include *vegetation mapping* as well as flood, waterlog and drought monitoring. Remote sensing minimizes the need for "traditional" survey in the field. It yields immediate, coherent and accurate results even for large areas at a relatively low unit cost. Richards [1] and McCloy [2] give detailed introduction to remote sensing and its applications.

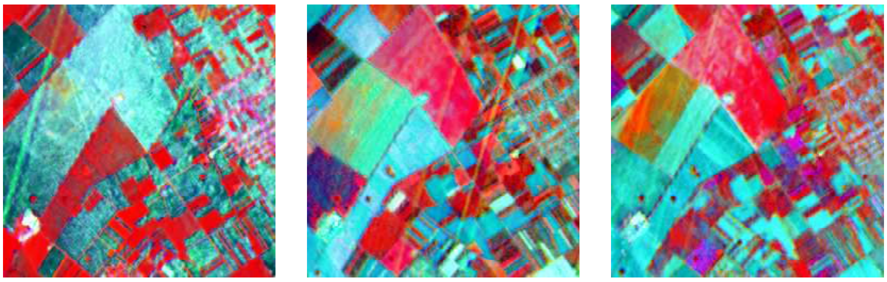
3. The traditional pixel-based classification

The task of thematic classification is to produce a digital thematic map of a certain area. The pixels of a thematic image usually refer to categories of land cover (classes). This is an important difference from satellite images, where pixel values contain the vector of measurement value: radiation intensities in spectral bands. The set of categories can be rather varying among the different applications: they can not only represent crop species, but they can show the severity of drought and they can make distinction between the areas affected by waterlog.

The input of classification methods consists of one or several satellite images. They usually use a thematic map, called reference data, describing the parts of examined area that are known in advance. Reference data are divided into two parts: training data (training areas) are used to determine the distributions describing land cover categories, while test data are the basis of accuracy assessment. The complex procedure of classification is usually not completely automatic; it is often improved by the interaction of a human expert.

Throughout this article, a *vegetation mapping* (crop mapping) application is taken as an example, where the task is to determine the crop species on agricultural areas with 25 m × 25 m spatial resolution (see Csornai et al., [3]).

The vegetation period and the progress of development of different crops can be rather varying throughout the year, but their reflectance often coincides in a given period. This is why images from multiple dates are necessary to create an adequate classification. Figure 2 shows a satellite image series of three dates, taken of the same area. The simplest way to involve multi-temporal data into the classification is when several images of the target area, having different acquisition dates, are "stacked together" to compose a multi-layer image.



(a) 06. 05. 2003. (b) 30. 06. 2003. (c) 11. 08. 2003.

Figure 2. A satellite image series of the sample area

It is a known observation in remote sensing that a large amount of pixels representing the same land cover category (e.g. crop species) show nearly normal distribution or can be approximated with several normal distributions. The following assumption is made as the principle of traditional classification task: each thematic category (e.g. wheat) can be described with the composition of appropriate *spectral subclasses*, each subclass having multivariate normal distribution in the multi-dimensional intensity space.

The pixel-based classification method described in [7] has been significantly modified. As a consequence, deep analogy can be observed between the pixel-based and segment-based classification. Together with accuracy assessment, the classification procedure consists of four major parts.

1. The first step in determining classes is *clustering*. This is an unsupervised procedure, in which no preliminary information (reference data) is used from the target area. Clusters are compact groups of the intensity space that characterize land cover categories. During this procedure, in each iteration the cluster map shows the assignment of cluster identifiers to pixels. In the procedure, the pixels of clusters with few elements and ones being far from every cluster are not classified. At the end of procedure

the mean vectors and covariance matrices (together: the signatures) of the clusters are calculated. Clusters determine the initial values of the spectral subclasses of land covers.

2. In the second step, in the *training phase* the aim is to assign a land cover category to each spectral subclass.

   In this step, the spectral subclasses that build up the distribution of pixels belonging to crops, as introduced above, are formed, starting from the clusters evolved in the first step. The input of this step is the original image, the map of training reference data and the cluster map. Its output is the signature set of spectral subclasses together with the assignment between them and land cover categories.

   Firstly, the pixels of image are assigned again to the clusters. This yields a new "cluster map". The assignment is done with the maximum-likelihood method using normal distribution functions. Every x pixel is classified to the cluster ω_k for which the following probability is maximum:

$$p(x|\omega_k) = (2\pi)^{-N/2}|\Sigma_k|^{-1/2}e^{-(x-\mu_k)^{\mathrm{T}}\Sigma_k^{-1}(x-\mu_k)/2} \tag{3.1}$$

   In practice, instead of the distribution function itself the natural logarithm of the above expression is calculated and is used to choose the appropriate cluster for pixels, in which the quadratic form $((x-\mu_k)^{\mathrm{T}}\Sigma_k^{-1}(x-\mu_k))$ is an additive member. Following the assumption that x is a random variable with normal distribution, the quadratic form has a χ^2 distribution with N degrees of freedom. It represents the confidence of x fitting a normal distribution with parameters μ_k and Σ_k. Comparing its value to the critical value belonging to the desired significance level, one can accept or reject the matching. In the implementation described in this paper, this test of hypothesis will be used several times.

   In this step, the test is the following: if, for a given pixel, even the maximum probability is small (i.e. according to the χ^2 test of hypothesis, the pixel does not fit into the cluster with a probability of 99%), then it is not classified.

   Next, the correspondence between clusters and reference areas is examined. For each cluster, the intersection of its points and the reference categories is determined. The next procedure assigns a label to every cluster:

   If there is not enough reference area compared to the cluster size
   Then
      If the cluster is large
      Then the cluster is *to be reclassified*
      Else the cluster is *to be abandoned*

Else
We search for the crop that intersects the most with the cluster
If this crop does not intersect sufficiently
Then the cluster is *to be reclassified*
Else
We search for all the relevant crops
If there is only one relevant crop
Then the cluster is *classified*
Else the cluster is *to be cut*

After this decision, we remember the only relevant crop for the *classified* clusters, and all the relevant crops for the clusters *to be cut*.

3. In the *classification phase* the pixels belonging to the labeled clusters are classified into land cover categories.

   Firstly, the pixels of clusters *to be reclassified* are classified with maximum-likelihood decision into one of the clusters that are *classified* or *to be cut*. The points not fitting into any cluster are abandoned.

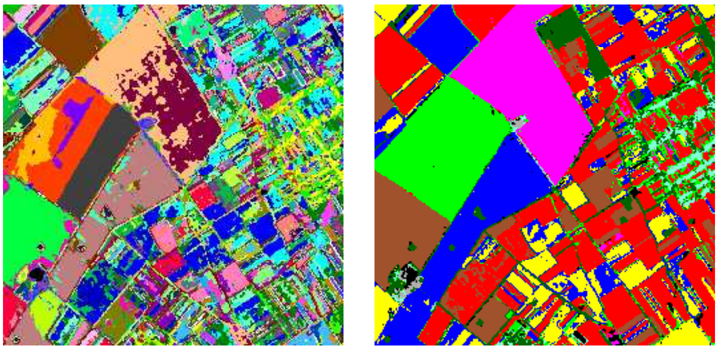
   Next, the signatures of the reference pixels belonging to the relevant crops within clusters *to be cut* are determined. The parameters of distributions assumed to be normal are estimated on the basis of the intersection of the cluster and the reference areas of relevant crops. Then the points belonging to the cluster are classified into one of these "subclusters" with maximum-likelihood decision, but at this point, the pixels not fitting into the subcluster are not abandoned.

   Finally, the pixels of *classified* clusters are assigned to the class of the only relevant crop.

   In the resulting image, the majority of pixels are assigned with a class. The pixels abandoned in the initial clustering, the ones of the clusters *to be abandoned* and the ones abandoned during the reclassification fall into the unknown category, that is they have not been classified.

4. Finally, an *accuracy assessment* is carried out with the usage of the test reference areas. In the case of high error rate, some of the previous steps are executed again with a modified parameter setting. (See the details in [8].)

It has to be noted that this "pixelwise" classification method completely ignores the identity or similarity of the neighbouring pixels in homogeneous areas (i.e. falling into the same agricultural parcel), as it uses only the intensity of pixels. Figure 3 illustrates the result of the clustering (a) and the classification (b) for a known area.



(a) Clustering (b) Classification

Figure 3. The result of pixel-based processing

4. The method of segment-based classification

A possible improvement of the traditional pixel-based classification method is to group certain pixels into so-called *segments* and to apply further classification steps to segments. The segmentation procedure described here is based on the method given by Kettig and Landgrebe [5], which was enhanced at several points (see e.g. Fekete and Farkasfalvy [6], László et al. [7]). Several further segmentation procedures are known, Schoenmakers [4] has written a detailed overview on them. The algorithm of segmentation is described in details in the next section.

In the variant of segment-based classification described in [7] the so-called *segment-based filtering* was applied after segmentation. This means that the value of each pixel was replaced by the average intensity value of the segment containing the pixel. It was followed by pixel-based clustering and classification, during which the pixels belonging to the same segment remained together. However, the information on deviation of the segments has been lost, which makes it hard to differentiate between segments that belong to different land cover categories, but have similar mean intensity.

In the method chosen in this paper, segments "pass through" the whole clustering and classification. The segments themselves are clustered and classified instead of tracing back the procedure to a pixel-based one. Due to this choice, less information is lost. This solution conforms to the model in which the distribution of intensity values within a segment can be approximated with a normal distribution. The mean (μ) and the covariance matrix (Σ) describing the distribution can be calculated from original intensity values of the satellite image.

The segment-based classification procedure has been improved at one further point. The classification of segments instead of pixels helps in the preservation of the homogeneities present in images, which stem from the properties of nature. However, this approach is not adequate enough to categorize the border points and heterogeneous areas necessarily present in images. This is why the classification method is finished with a step in which the categorization of every point is revised. The automatic procedure for the assignment between clusters (or spectral subclasses) and thematic categories, presented in Section 3 (Step 2 and 3), is applied also in the segment-based approach.

5. The segmentation of images

In [7] a method was presented to take into account the position of pixels — in this case, information derived from the adjacency — in the classification procedure. To achieve this, a segmentation procedure was applied before the "classical" clustering and classification. A *segment* is a contiguous set of adjacent, spectrally similar pixels. The result of segmentation is a thematic map, called the *segment map*, which contains the number of the respective segment for each point.

Several significant improvements have been made on the method described in [7]. Firstly, the dependence upon the processing order was reduced. Secondly, the borders of segments can be more refined, which results in segments better conforming to the real status of the surface. The aim of the algorithm is to delineate spatially contiguous and statistically homogeneous areas. Adjacent pixels that probably belong to the same land cover — according to an appropriate similarity criteria — are grouped into the same segment.

In the first step of the segmentation algorithm, the image is subdivided into cells with 2×2 size. Then a decision is made on each cell whether it can be considered homogeneous. A cell is homogeneous if the following inequality holds in every band (where n is the number of pixels in a cell; in this case, $n = 4$):

$$\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{(n-1)\bar{x}^2} \leq C_H. \tag{5.1}$$

The condition means that in every band, the deviation remains under a certain limit compared to the average intensity. The pixels of inhomogeneous cells are not categorized into segments and a region-growing algorithm is run on the homogeneous cells.

The algorithm passes through the rows of cells from up to down, and cells are

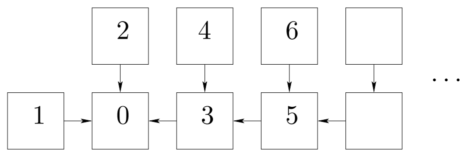


Figure 4. The order of the contraction of cells

taken from left to right within a row. For each cell, a test is made whether it can be connected to an existing cell, based on a contraction rule. Due to the order in the examination of cells, in Figure 4 cells 1, 2, 4, 6 are already the members of some cell (they may form a segment in themselves). In the following, a decision is made to which of them cell 0 can be connected. First all the possibilities are examined, then one or more of the possible connections are chosen.

Firstly, it is examined whether cell 0 can be connected to cell 1 or 2, as shown in the figure.

Next, a decision is made whether cell 3 can be connected to the segment containing cell 4, and if so, whether cell 0 can be connected to this new segment (3 plus the segment of 4).

$6-5$, $6-5-3$ and $6-5-3-0$ connections are examined similarly (assuming the preceding conditions are met). Looking ahead to the right can be arbitrarily extended (depending on a runtime parameter), as is illustrated in the figure.

Among the connection possibilities examined the one with the smallest distance between the segment and the cell is chosen. If intermediate cells are parts of a connection, then during the consecutive contractions, the maximum segment-cell distance is taken into account. If neither of the above connections is possible, then a new segment is initiated with the current cell.

The decision on the possible contractions is made on the basis of ANOVA-like criteria determined by the means and standard deviations of segments. Let x and y denote a sample (segment) with m and n elements (points), respectively, and let z mean the distribution resulted from the contraction of x and y. The following quantities are calculated in each band:

$$A_x = \sum_{i=1}^{m}(x_i - \bar{x})^2, \qquad A_y = \sum_{i=1}^{n}(y_i - \bar{y})^2, \qquad A = A_x + A_y, \tag{5.2}$$

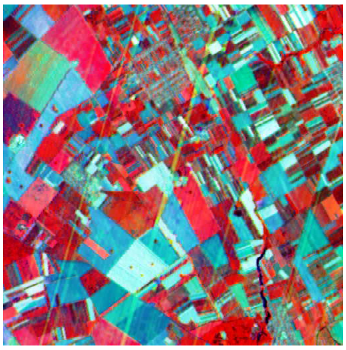
$$B_x = \sum_{i=1}^{m}(x_i - \bar{z})^2, \qquad B_y = \sum_{i=1}^{n}(y_i - \bar{z})^2, \qquad B = B_x + B_y. \tag{5.3}$$

Segment contraction is allowed with respect to a certain band if both of the following inequalities are met for given C_1 and C_2 values. Two segments are allowed to be contracted if inequalities (5.4) and (5.5) are met in every band.

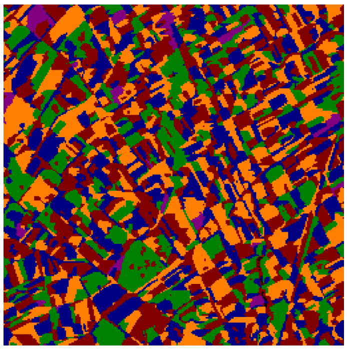
$$(A/B)^{(m+n)/2} \geq C_1, \tag{5.4}$$

$$\left(\frac{(A_x/m)^{m-1} (A_y/n)^{n-1}}{\big(A/(m+n)\big)^{m+n-2}} \right)^{1/2} \geq C_2. \tag{5.5}$$

As a result of an appropriately parametrised decision procedure, a segment map is obtained where the connected parts expectedly belong to the same land cover category. On the other hand, one land cover category can be composed of several segments — either lying far from each other or adjacent ones. A segment map of the previously introduced sample area is shown in Figure 5 together with a satellite image, so that they can be easily compared.



(a) Satellite image



(b) Segment map

Figure 5. The result of segmentation

6. Segment-based clustering

In an earlier phase of the work (see [7]) segment-based classification was traced back with an appropriate substitution to the application of pixelwise clustering and pixelwise classification, as was mentioned in Section 4. Since then, a segment-based clustering procedure has been developed, which categorises segments instead of pixels.

The Isodata clustering algorithm has been modified so that it deals with segments. The general scheme of this algorithm consists of the following steps:

Step 1 Initial cluster centres are chosen
Step 2 Segments are assigned to the nearest cluster centre
Step 3 Small clusters are abandoned
Step 4 Clusters near to each other are contracted
Step 5 Large clusters are subdivided
Step 6 If the stopping criterion is not met, then the algorithm is continued from Step 2 with new cluster centres derived from the current clusters

In the algorithm there are several possibilities in the choice of applied methods, distance functions and parameters.

In Step 1, initial cluster centres are chosen randomly, according to a normal distribution that approximates the best all the intensity values present in the image. Such a random point is obtained if one adds to the empirical mean vector an independent vector of standard normal distribution multiplied with the Cholesky-decomposition of the empirical covariance matrix.

In Step 2, segments are assigned to the centre with the minimum Euclidean distance from the points of segment (in the intensity space, using quadratic mean). However, if even the minimum distance is higher than a certain threshold, the segment is not assigned to any cluster. The mean Euclidean distance between centre x and segment ω is

$$d(\omega, x) = \sqrt{\sum_{k=1}^{N} \mu_k^2 - 2\mu_k x_k + x_k^2 + \sigma_{kk}} \;. \tag{6.1}$$

Step 3 abandons clusters with number of elements less than a threshold.

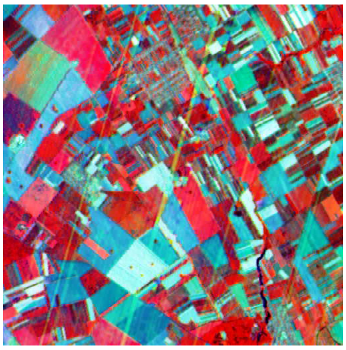
In Step 4, clusters with similar intensities are contracted. To achieve this, the separability of the empirical distributions determined by the clusters is examined (distances are meant in the intensity space). To measure this between clusters ω_i and ω_j, the Bhattacharya distance is used:

$$d(\omega_i, \omega_j) = \frac{(\mu_i - \mu_j)^{\mathrm{T}} \left(\frac{\Sigma_i + \Sigma_j}{2}\right)^{-1} (\mu_i - \mu_j)}{8} + \frac{1}{2} \ln \frac{\left|\frac{\Sigma_i + \Sigma_j}{2}\right|}{\sqrt{|\Sigma_i||\Sigma_j|}} \tag{6.2}$$

In the current algorithm, the subdivision in Step 5 is not applied. With the choice of appropriately many initial cluster centres, the occurrence of clusters having significant intersection with several land cover categories can be minimized or eliminated.

The algorithm stops after a pre-defined number of iterations. Another stopping criterion, the movement of centres, could be applied: the algorithm would stop if the movement of cluster centres, using an appropriate norm, is small within two consecutive iterations.

The normal distributions in spectral space, determined by the algorithm, are considered the result of clustering. They are described with the mean vectors and covariance matrices (see the first step of the classification algorithm in Section 3). Certain pixels do not take part in the formation of signatures: first, the points that were out of scope of segmentation (that is, the points that fell into inhomogeneous cells), second, the points of segments far from all clusters. An illustration for the result of segment-based clustering is shown in Figure 6.


(a) Satellite image

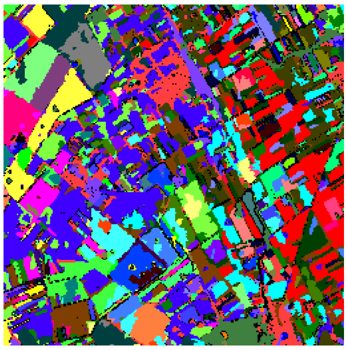

(b) Cluster map

Figure 6. The result of segment-based clustering

7. The thematic classification of segments

The aim of segment-based classification is the determination of the distributions constituting the land cover categories. As mentioned, several distributions may build up a thematic category, and this is why the term "spectral subclass" is used. In the first step the segments of image are again assigned to the evolved clusters, using their empirical distribution. The assignment is done with the maximum-likelihood method, as in the case of the pixel-based approach.

The logarithmic average of probabilities over the pixels of segment is used as discriminant function in the maximum-likelihood decision

$$\mathrm{E}(\log P(\omega_s|\omega_k)) = \tag{7.1}$$

$$= \frac{\sum_{x\in\omega_s} -\frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma_k| - (x-\mu_k)^{\mathrm{T}}\Sigma_k^{-1}(x-\mu_k)/2}{n_s} =$$

$$= -\frac{N\log(2\pi) + \log|\Sigma_k| + \mathrm{tr}(\Sigma_k^{-1}(\Sigma_s + \mu_s\mu_s^{\mathrm{T}})) - 2\mu_k^{\mathrm{T}}\Sigma_k^{-1}\mu_s + \mu_k^{\mathrm{T}}\Sigma_k^{-1}\mu_k}{2}.$$

The average of χ^2 values over the pixels is used in the χ^2 decision

$$\operatorname{tr}(\Sigma_k^{-1}(\Sigma_s + \mu_s\mu_s^{\mathrm{T}})) - 2\mu_k^{\mathrm{T}}\Sigma_k^{-1}\mu_s + \mu_k^{\mathrm{T}}\Sigma_k^{-1}\mu_k. \tag{7.2}$$

The algorithm assigns all the segments to a cluster, except the ones not belonging to any cluster with 99% probability, according to the χ^2 test. This yields a new "cluster map" instead of the original one.

Next, the intersection of reference areas and the cluster map is calculated. Each cluster is assigned by a label with the same procedure used in the pixelwise case (see Section 3, second step). The label of clusters can be *to be abandoned*, *classified*, *to be reclassified* and *to be cut*. The processing of clusters, depending on labels, is formally the same as in the pixelwise case. It has to be noted that during the assignment between segments of clusters *to be cut* and intersections of clusters and reference data categories, the logarithmic discriminant function introduced above is used again.

After these steps the primary classification of image has evolved. Its result is that almost all the segments are assigned to one of the land cover categories. It may happen that a segment draws in a pixel not fitting to its category. Another possible drawback is that the grouping of pixels into cells makes the handling of border points coarser. Because of this, the primary classification is revised by a pixelwise χ^2 test of hypothesis at a level of 99%, implicitly applying the test for the subclusters of clusters *to be cut*.

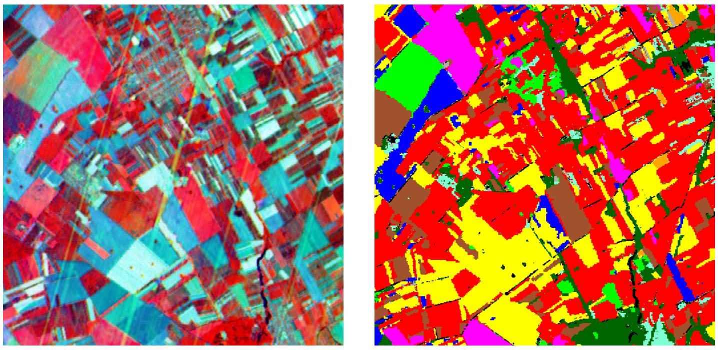
Finally, the so-called pointwise correction follows: the pixels fallen out during the revision of segmentation, clustering and classification are assigned with maximum-likelihood method to a cluster that is *classified* or *to be cut* (or into one of its subclusters), and through this mapping, into a thematic category. However, the χ^2 test at a level of 99% is also applied for this categorization.

For all the pixels categorized after these steps, the assignment of the thematic category is reasonable. The test reference areas are used in accuracy assessment, as in the case of the pixel-based case. Figure 7 illustrates the result of the segment-based classification for the sample area introduced earlier.

8. Conclusions and research perspectives

This article has presented possible developments for several steps of thematic classification, improving the final result both qualitatively and quantitatively.

Compared to the method described in [7], within the algorithm of segmentation the conditions of joining different segments were made more flexible and symmetrical. Owing to this, the result is more realistic and is less dependent



(a) Satellite image (b) Final thematic map

Figure 7. The result of segment-based classification

on the processing order of cells, while the efficiency has been kept. Besides, the algorithm has become less sensitive to the parameters (for example, C_1 and C_2 in (5.4) and (5.5)).

The most conspicuous result of applying clustering for segments instead of pixels is the increase of speed: the number of objects to be clustered decreases by several orders of magnitude. Furthermore, while the deviation of segments was ignored because of the segment-based filtering, now this kind of information is also utilized. The authors have implemented a version of Isodata clustering that is more robust if spectrally isolated points are present.

As a quantitative evaluation of classification, it can be stated that the thematic accuracy is usually higher when using segment-based methods. With appropriately chosen parameters the global accuracy can be increased by about 2-3% on average. In the following, a typical confusion matrix is presented in the pixel-based (Table 1) and in the segment-based (Table 2) case.

The result of classification is also improved by the possibility of allowing the separated processing of pixels not fitting to their neighbourhood or to the majority of the image, which might otherwise distort the result.

In agricultural applications, the advantages of segmentation are best seen in the distinction between spectrally similar arable land crops. This is why this method utilizes the regularity of parcels resulted by the cultivation structure. For example, making distinction between maize and sunflower based solely on their spectral characteristics is rather difficult: in the case of common pixel-based classification, it might happen that an area belonging to one parcel contains both pixels classified as maize and ones classified as sunflower, in irregular arrangement. However, within a heterogeneously developed parcel, segmentation can better “keep together” the pixels with different intensities — see Figure 8. Therefore, more realistic classification result is obtained locally, in the interior of

Table 1. The confusion matrix of a pixel-based classification

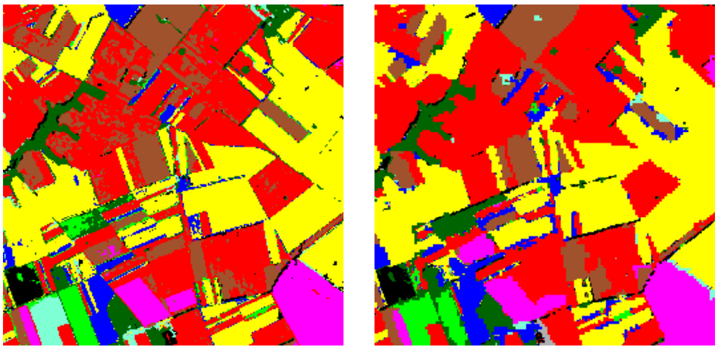
	C0	C1	C3	C4	C10	C12	C13	C14	C22	C27	C40
C1	392	9394	128	93	0	0	0	0	0	22	0
C3	14	1681	522	0	0	0	0	0	2	7	0
C4	51	325	0	207	0	0	0	0	0	0	0
C10	227	218	0	0	3650	1	19	0	73	5	0
C12	19	0	0	0	2	5702	0	0	0	4	6
C13	26	0	0	0	72	43	11476	0	3	0	0
C14	0	0	0	0	0	0	0	981	0	0	0
C22	0	3	0	0	20	0	2	0	2551	17	8
C27	0	3	0	0	0	0	0	0	0	484	0
C40	3	1	30	0	32	0	0	0	13	0	5381
Overall accuracy											91.8%

Table 2. The confusion matrix of a segment-based classification

	C0	C1	C3	C4	C10	C12	C13	C14	C22	C27	C40
C1	121	9352	513	32	0	0	0	1	3	7	0
C3	16	57	2142	1	0	0	0	0	6	4	0
C4	20	323	0	238	0	0	0	0	2	0	0
C10	190	10	2	0	3816	84	10	0	59	22	0
C12	7	0	7	0	1	5701	0	0	0	8	9
C13	25	0	0	0	6	73	11436	0	75	0	5
C14	0	0	0	0	0	0	0	981	0	0	0
C22	2	2	1	0	5	7	0	0	2582	1	1
C27	1	4	0	0	0	2	0	0	10	470	0
C40	1	0	83	0	0	0	0	0	0	0	5376
Overall accuracy											95.9%

the parcels. Nevertheless, at the border of different land covers it may happen that the result of pixel-based classification is more appropriate. In summary, due to the dominance of interior pixels, using the segment-based method usually increases the global accuracy.

In this article, a crop mapping application was taken as an example. Indeed, during the development and the explanation of methods the properties of agricultural areas were taken into account. However, segmentation can also be used in other thematic classification applications, for example forest mapping, waterlog monitoring and general mapping of land cover categories (not restricted to



(a) Pixelwise case (b) Segmentwise case

Figure 8. The decrease in confusion as the result of segmentation

agricultural areas).

The method was developed to work with optical satellite images with similar parameters, especially, with identical spatial resolution. However, it can also take other kinds of remote sensing data as input (e.g. aerial photos, radar images), if identical pixel size is provided, possibly with the resampling of input data. Furthermore, with some modifications, prior resampling can be avoided, and the handling of different resolutions can be integrated into the program.

In the classification phase reference data — used in the form of thematic raster maps — is usually derived from a vector layer resulted from e.g. GPS survey. Other vector layers can be similarly integrated, which may increase the classification accuracy.

In its present state, the segmentation procedure uses solely the input raster images themselves to delineate segments, but it is possible to involve other prior knowledge to improve the results. With a method similar to the one used in the classification phase, even vector layers can be used. The use of cadastral data seems to be promising in agricultural and other land cover mapping applications, but it can lead to errors if the borders of official administrative cadastral parcels do not match the actual cultivation structure. In countries using physical or farmer blocks as the reference units of Land Parcel Identification System (the reference system of agricultural subsidies), the layer of block boundaries may effectively complement the input satellite images. If recent topographic maps are available in vector form, certain layers of them can also be used as an aid in segmentation. Basically, these kinds of vector data are appropriate to give "hints" to the program about the location of segment boundaries. They can improve the accuracy, and, as they usually limit looking ahead in the procedure (see Section 5), and in general, the size of segments, the method can also be made more efficient with their usage.

Thorough testing of the possibilities and advantages of introducing preliminary geographical data into the classification is the subject of further research.

References

[1] **Richards J.A.,** *Remote sensing, digital image analysis – An introduction*, Springer Verlag, 1993.

[2] **McCloy K.R.,** *Resource management information systems: Remote sensing, GIS and modelling* , 2nd edition, Taylor & Francis, 2006.

[3] **Csornai G., Dalia O., Farkasfalvy J. and Nádor G.,** Crop inventory studies using Landsat data on large area in Hungary, *Applications of Remote Sensing in Agriculture,* Butterworths, 1990, 159–165.

[4] **Schoenmakers R.,** *Integrated methodology for segmentation of large optical satellite images in land applications of remote sensing*, Joint Research Centre, 1995.

[5] **Kettig R.L. and Landgrebe D.A.,** Classification of multispectral image data by extraction and classification of homogeneous object, *IEEE Transactions on Geoscience Electronics*, **14** (1) (1976), 19–26.

[6] **Fekete I. and Farkasfalvy J.,** Automatic segmentation of multispectral digital images, *5th Conference of Program Designers,* ELTE, Budapest, 1989. (manuscript)

[7] **László I., Pröhle T., Fekete I. and Csornai G.,** A method for classifying satellite images using segments, *Annales Univ. Sci. Budapest. Sect. Comp.*, **23** (2004), 163–178.

[8] **Nádor G., Csornai G. and Kocsis A.,** A tematikus pontosság mérésének módszerei a távérzékeléses növényterület felmérésben, *VII. "Földfelszíni és meteorológiai megfigyelések a világűrből" szeminárium,* Budapest, 1997, 198-205. (Methods of accuracy assessment of thematic vegetation mapping by remote sensing, *7th Seminar on Earth and Meteorological Observations by Satellites,* Budapest, 1997, 198-205. (in Hungarian))

I. László
Faculty of Informatics
Eötvös Loránd University
Pázmány Péter sétány 1/c.
H-1117 Budapest, Hungary
and
Institute of Geodesy, Cartography
and Remote Sensing
Remote Sensing Centre
Bosnyák tér 5.
H-1149 Budapest, Hungary
listv@inf.elte.hu

B. Dezső and I. Fekete
Faculty of Informatics
Eötvös Loránd University
Pázmány Péter sétány 1/c.
H-1117 Budapest, Hungary
{deba,fekete}@inf.elte.hu

T. Pröhle
Faculty of Science
Eötvös Loránd University
Pázmány Péter sétány 1/c.
H-1117 Budapest, Hungary
prohlet@cs.elte.hu