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On the importance of using knowledge and the manner of incorporating it into the image analysis

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Abstract

During the last 3 decades, many remote sensing image analysis methods have been proposed by the researchers including the statistical approaches, knowledge based and model based algorithms. Beside the accuracy improvement that has been reached by these methods, it has been approved that although this is important to make use of the knowledge about the objects and processes but the most important thing is how to use these knowledge in the image analysis. In this paper we are going to show that using knowledge of land cover objects and processes in a proper manner can improve efficiently the accuracy of the image analysis. During this study, some aspects of the traditional maximum likelihood classifier are examined and a method for incorporating knowledge of objects and processes into the image analysis is introduced.

Key words: Knowledge, Model Based Image Analysis, Maximum likelihood Classification, Remote Sensing.

1. Intoroduction

There are various classification methods, which have been developed so far, to obtain better results from the image interpretation and classification. Number of these methods exceeds two hundreds (Roudys *et al.*, 1991). We can see that the newer methods tends to use more external information in the inference process than the older methods which, use only the spectral information contained in the image for image interpretation.

So far, pixel-based classification methods have been the most common methods for the analysis of the remotely sensed images. From the result point of view they have various problems that make them imperfect with limited accurate results. They have some sensitivity to the various features of the image data such as mixed pixels, noisy pixels, sample size of the classes, radiometric overlaps of the classes and so on. These affect the results of the pixel-based classification methods. To overcome these problems researchers have proposed many solutions including context classification (Richards and Jia, 2006), knowledge based classification (Gao, 2009), model based image classification (Abkar et al., 2000).

One group of the advanced classification procedures is called knowledge-based methods. These methods are designed to be able to use different external knowledge about the scene from various sources. Our knowledge can be incorporated into the decision making process in various forms such as rules (Richards and Jia, 2006) and semantic nets (Growe, 1999). Knowledge-based classifications are powerful methods that are able to work with multisensor, multitemporal and multisource data and then improve the classification accuracy notably.

Knowledge-based classification methods use external knowledge to modify their performance and results. Today there are many sources of information about the earth surface and various sciences are active in this field. In the area of remote sensing, multitemporal, multisensor, multisource data are also available for different parts of the earth. Additionally there is a motivation to provide the GIS for the various parts of the countries and they can be potentially a powerful source of data and/or knowledge for knowledge-based methods. More advance knowledge-based methods are capable to accept various forms of the information and then has more flexibility than previous methods.

Although it is already approved that knowledge based methods can lead hopefully to a higher accuracy using knowledge in the analysis process; but most of knowledge based methods are bottom-up process because they don't directly use the relevant object specific knowledge (or object model) in the scene; rather they apply generic knowledge for guiding the classification and analysis (Abkar, 1999, Abkar et al., 2000). In fact they are not the specific task solvers but they start at the lower levels of the data and finally try to give the object descriptions. As a consequence, they can not use all benefits of the integration of remote sensing and GIS (as a strong source of the knowledge) because that GIS databases work with objects as entities. For this aim top-down methods are more adequate. Top-down modeling approaches are very important and powerful image analysis methods. They use available information in an appropriate manner to yield the best results. In fact using external knowledge only, can't give the better results surly; and the manner in which this knowledge is used is very effective. As Clark et al, (1993) reported, it is not sufficient that simply obtaining extra information for classification, its use must be modeled appropriately.

It can be shown that Bayesian decision rule minimizes the average probability of error over the entire classified data set, if all the classes have normal (Gaussian) probability density function (Richards and Jia, 2006, Theodorodis and Koutroumbas, 2008). However, the normal probability model for probability distributions is not a reliable assumption (Mulder, 1994) and this is a doubtful assumption for data behavior. Maximum-likelihood classifier (Mather, 2010) has some other drawbacks but it is a relatively powerful method for information extraction from remotely sensed images. We'll use some simple external knowledge to improve the accuracy of the classification. During this study we are going to show that using external knowledge in a proper manner in image analysis enable us to overcome some drawbacks of the traditional classifiers.

2. The Bayesian MBIA method

The goal in this method is to select per geometric area segment the class with the maximum probability, provided that the risk of misclassification is lower than a threshold of expected cost (of misclassification) and support for the single class per segment hypothesis. If the expected cost is too high then the geometric hypotheses have to be modified (for example, through a re-segmentation).

Then, the goal is defined as maximum probability over object parameters in:

Prob(Object_class, Object_geometry | data(band, x, y), Source, Path)

Ignoring for the moment the Source and atmospheric Path models our goal reduces to:

Prob(Object({x,y})_class| Object_geometry, data(band,x,y)).

For reasons of comparison we first calculate Prob(Class(x,y) | data(band,x,y)), which is the classical per 'pixel' result.

With a GIS providing Object({x,y}) in the form of a unique segment index S(x,y) there are now two ways to proceed: In the Model Based Image Analysis (MBIA) method (Abkar, 1999) we study the distribution Freq(Class, S), if the distribution has a single peak for a class then we take the average per segment S of Prob(Class(x,y) | data(band,x,y)), producing a likelihood vector Prob(Class, S), else, if there are more than one peak then the geometric hypothesis has to be updated if likelihoods are almost equal, then the risk of misclassification may be above an acceptable threshold (Abkar,1999).

3. Examples by Synthetic Images

In this section we will show the abilities and various characteristics of mentioned approach model-based image analysis versus the traditional maximum-likelihood classification method. We discuss the different parameters, which are effective in the maximum likelihood classification procedure. These are including radiometric overlap effect, kind of distribution and effects of prior probabilities. But firstly we show some simple example of the functionality and performance of the model-based image analysis. In order to have a controllable process and reliable investigation, we perform our experiments using generated synthetic images.

For generation of all images we assumed that our data has a known distribution (here Normal distribution; except in the case of estimation of the effect of various distribution types for data). Using some real mean vectors and covariance matrices we generated the pixel values, for the test images. Covariances between all of the bands were assumed to be zero in the all cases. For each image 3 bands were generated. In the maximum-likelihood classification, the priors were assumed to be equal. It must be mentioned that all the experiments and conclusions, which will be obtained using synthetic images, are reliable and correspond to tests with the real images. We have tried to simulate the real situation and involve the various important factors in imaging process in the generation of the synthetic images. For example large values of radiometric overlaps can compensate different errors, which are usually in the imaging process.

In the following experiments, we are trying to examine various aspects of the traditional classification methods and the effect of using knowledge using the method mentioned in the section 2. The first case deals with the effect of using the knowledge in the image analysis. In the second experiment a similar case but with different geometry and number of classes, is examined. Case 3 proceed on the radiometric or spectral overlap. Case number 4 deals with this fact that the normal distribution violence can lead to accuracy degradation. In the case 5 the prior probability and its role in the Bayesian classification procedures is investigated.

3.1. Experiment 1: Embeded polygons with different classes

In this experiment, the ground truth includes 2 polygons with different classes. The upper left coordinate of the inner square is 3, 3 and the lower right coordinate is 14, 14. The size of the whole map is 18×18 pixels (Figure 1).

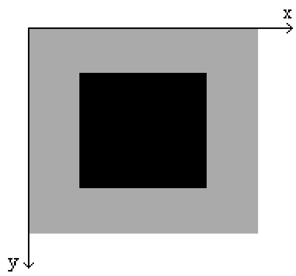

Figure 1. State of the boundaries of two classes (18×18 pixels)

In this case we can model these two classes with four boundaries, which two edges are horizontal and others are vertical. We assume a coordinate system, which its origin is the top left of the image and x-axis of it will be horizontal and y-axis is aligned to the columns. (See Figure 1). Thus we must only estimate one parameter for each edge in this coordinate system including x or y coordinate. Three generated bands (using signatures in Table 4.2) of the image (Figure 2) show the radiometric overlaps of classes.

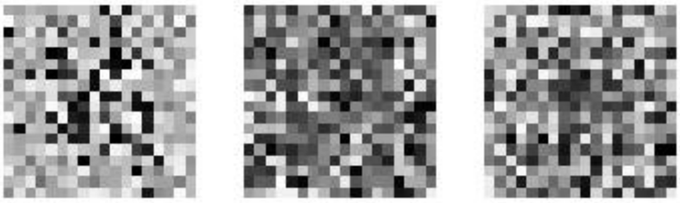

Figure 2. Three bands of the image in Figure 1 using signatures in Table 1 (128×64 pixels)

The result of maximum likelihood classification and MBIA (Section 2) are shown in the Figure 3. However as this figure shows, maximum-likelihood classification cannot yield good geometric description of the scene and there are many individual small segments that cannot give reliable object recognition. Interpretation of these dispersed segments is very difficult and in a view of thematic map generation, it is not a map required by the users of GIS.

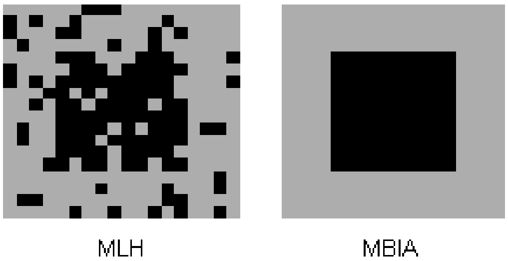

Figure 3. Maximum–likelihood classification and model based image analysis (MBIA) results for image shown in Figure 1. MBIA could find the true geometric parameters and retrieves the object geometry as it is.

The overall accuracy of the maximum-likelihood classification (Figure 3) is 81.5%. It seems that it is a good result but clearly we have lost the shape of the objects presented in the scene. Also a general measure of accuracy like overall accuracy cannot give a perfect and proper assessment of the results. Additionally some factors that can disturb the results of the maximum-likelihood classification were not involved in this experiment (see the next experiments). Using the MBIA we could find the true values for the object geometry. Note in this case we just apply this knowledge that the inner polygon is a rectangle. Based on the obtained parameters we reconstruct the two classes using the known model (Figure 3).

3.2. Experiment 2: Three classes with 2 separating edges

If we have more than two classes (the common case in many of the real applications), obviously the complexity and the challenges will be increased. More radiometric overlap leads to the more ambiguity and decision about the priors, in these cases is a critical issue. For the aim of proving our idea and the problems, which may be faced, in this experiment we assume a scene with three classes including two separating edges. Figure 4 illustrates the ground truth for this case study with the size of 16×20 pixels. The defined edges are in the middle of the rows and columns and therefore, the area of the 2 top squares are equal.

Figure 4. There are three classes in the scene that two edges separate them (16×20 pixels). Class A, B, C are represented by light gray, black and dark gray colors, respectively (Vertical edge is in column number 10 and horizontal edge is in row number 8).

For generation of the pixel values we used values in the Table 1 as signatures for these classes. The generated bands are shown in Figure 5. From the Table 1 it is clear that radiometric overlaps became higher than the previous case and it is expected that accuracy of the classification be lower than the previous cases. As Figure 5 illustrates, visual recognition of the classes, is very difficult and erroneous. The result of the maximum likelihood has 60% overall accuracy and classified image is shown in Figure 6 (equal priors assumption). Obviously, this noisy map is not the desired result and it is not proper for many applications. In fact, the geometrical information (straight edges) is lost in the classified map.

Table 1. Signatures of the 3 classess in the Figure 4**.**

BANDS	MEASN			STD			RADIOMETRIC OVERLAP (%)		
	Class A	Class B	Class C	Class A	Class B	Class C	A-B	A-C	B-C
Band 1	44.3	49.6	51.2	4.14	5.48	4	57	39.6	80.8
Band 2	61.8	61.2	63	6.73	4.67	5	82.2	84	85
Band 3	67.8	61.5	64	7.32	7.05	6	66	76.3	83.6

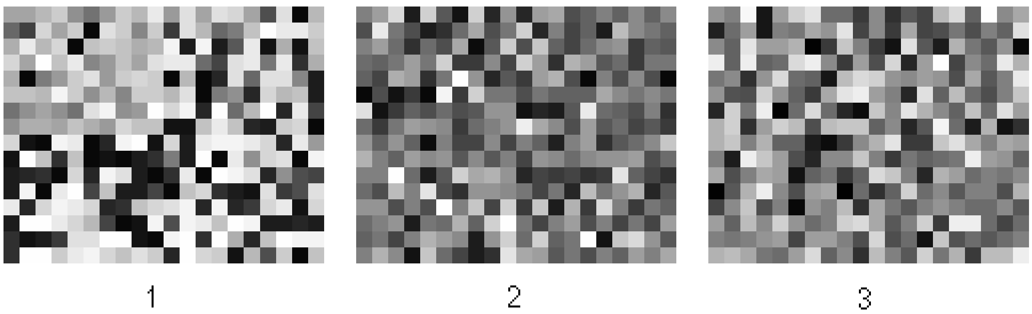

Figure 5. Three bands of the synthetic image with 3 classes (Using signatures in Table 1)

But what happens for model-based image analysis method? It is a good example to show that it is important to use external knowledge and take a well designed strategy to incorporate this knowledge in the process of image classification. For this purpose we assume a model with two parameters, which can be varied from 1 to 16 for horizontal edge and from 1 to 20 for vertical edge. The MBIA method found the best parameters as shown in Table 2.

Table 2. Results of the MBIA

Horizontal Edge	*Vertical Edge*	*Correspond Cost*
8	11	0.502

From Table 2 it is clear that the horizontal edge exactly has been found but true place of the vertical edge (10) has been found as 11. Hence we have an error in estimating the vertical edge. It may have two reasons: firstly the vertical edge (8 pixels) has a shorter length than horizontal edge (11 pixels) and as it is well known, geometry has more meaning with a larger length (object size relative to the sensor resolution!), in a raster spatial data model. Then for longer edge we can obtain better results for modeling. Second reason, which is a common problem in many cases, is related to radiometric overlaps of the land cover objects that is increasing with the number of classes; in this case they are increased and hence cause the ambiguity in the radiometric evidences.

Evidences are a major part for the cost estimation and wrong evidences lead to the wrong estimates. Then it can be concluded that in any method achieving the optimal result depends on the overlap of the probability density functions (Abkar and Mulder, 1996). However, model based image analysis method shows more stability against this error. We will investigate this on the following experiments.

However using the external knowledge in a proper manner (here MBIA) we can obtain the reliable, and more accurate results, but it is obvious that such algorithms cannot give the perfect results in all cases, especially when its inputs are erroneous. However, we are expecting more accurate results.

In the following we examine the stability of the model based image analysis against some common errors, which affect the results of the classification method. We have chosen the most important and essential aspects, which are involved in many cases, and are common problems in all of the classifiers.

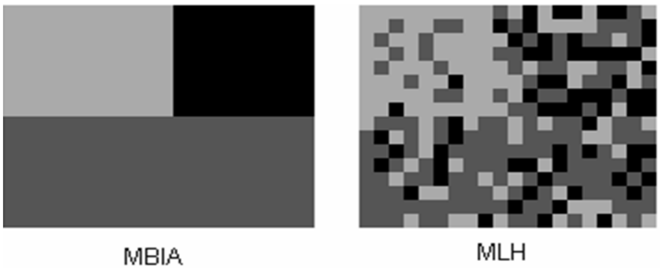

Figure 6. MBIA and MLH results

3.3. Experiment 3: Radiometric overlap effect on the classification results

Radiometric overlap is one of the major sources of the errors, which critically affect the classification results. It arises from the various parameters and aspects of the remote sensing system. Some of these are referred to the data acquisition process. For example some land cover materials have the same reflectance character and then their pixels values will be very similar. Atmosphere also influences the electromagnetic wave and causes some errors in the data acquisition process. It can be appear in the form of the radiometric overlaps between different classes, ultimately. Training stage in the supervised classifications also can be a potential source for the radiometric overlap if it dose not done carefully.

However classification methods particularly, parametric versions are very sensitive to this problem and their results are governed by it. For assessing the effect of the radiometric overlap on maximum-likelihood classification and in the presence of the knowledge we have perform some tests.

Let assume the case in which we have 2 classes separated by a straight edge (Figure 7), and will change the signatures of the classes. Then we change the radiometric overlap between the classes by changing the signature values of the classes according to Table 4.5. On the basis of these parameters we designed 9 cases, as follows below:

1. Original case
2. Reduce the radiometric overlap by increasing the distance between the means values of the 2 classes (in band 1 only)
3. Increase the radiometric overlap by reducing the distance between the mean values of the 2 classes (in band 1 only)
4. Increase radiometric overlap by reducing the distance between the mean values of the 2 classes (for all bands)
5. Reduce the radiometric overlap by reducing the standard deviations (in band 1 only)
6. Increase the radiometric overlap by increasing the standard deviations (for band 1 only)
7. Complete overlap (for band 1 only)
8. Complete overlap (for band 1, and 2)

9. Complete overlap (for all bands, all the signatures for the two classes are the same)

Corresponding values are presented in the Table 3.

Figure 7. Truth map with the two classes with a common edge (128×64 pixels)

The overall accuracy of maximum-likelihood for all the scenarios and the corresponding estimated edge parameters are presented in the Table 4. From these values it is clear that with increasing the radiometric overlap, accuracy of the traditional maximum-likelihood is decreased, the fact that we have expected for the parametric classification like maximum-likelihood classifier. For case 2, maximum-likelihood yielded a perfect result (100 % overall accuracy), since the class probability density functions have no overlap (Table 3). It is clear in the real case this is impossible because of various error sources that are in the acquisition and processing stage as well as the spectral similarities between the land cover objects. Therefore, we expect some radiometric overlap between classes.

Table 3. Signatures of the two classes A and B, for the nine scenarios in the experiment 4.

Case	Bands	Mean		Standard deviation		Radiometric Overlap (%)
		Class A	Class B	Class A	Class B	
1	1	44.3	49.6	4.14	4.48	57
	2	61.8	62.2	6.73	4.67	82.2
	3	67.8	61.5	7.32	7.05	66
2	1	44.3	149.6	4.14	5.48	0
	2	61.8	62.2	6.73	4.67	82.2
	3	67.8	61.5	7.32	7.05	66
3	1	44.3	45.6	4.14	5.48	83.5
	2	61.8	61.2	6.73	4.67	82.2
	3	67.8	61.5	7.32	7.05	66
4	1	44.3	45.6	4.14	5.48	83.5
	2	61.3	61.2	6.73	4.67	82.5
	3	62.8	61.5	7.32	7.05	92.5
5	1	44.3	49.6	2.14	3.48	33.5
	2	61.8	61.2	6.73	4.67	82.2

	3	67.8	61.5	7.32	7.05	66
6	1	44.3	49.6	6.14	7.48	68.8
	2	61.8	61.2	6.73	4.67	82.2
	3	67.8	61.5	7.32	7.05	66
7	1	44.3	44.3	1.14	4.14	100
	2	61.8	61.2	6.73	4.67	82.2
	3	67.8	61.5	7.32	7.05	66
8	1	44.3	44.3	4.14	4.14	100
	2	61.8	61.8	6.73	6.73	100
	3	67.8	61.5	7.32	7.05	66
9	1	44.3	44.3	4.14	4.14	100
	2	61.8	61.8	6.73	6.73	100
	3	67.8	67.8	7.32	7.32	100

Table 4. Overall accuracies (MLH) and the estimated parameters for MBIA

Case	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
Overall accuracy (%)	77.6	100	69.85	61.82	85.67	74.15	69.78	65.75	51.56
Estimated parameter	32	32	32	32	32	32	32	32	0

Case 7 and 8 are also exceptional cases. In such a situation, where there is no discrimination between classes, all the classifiers would fail. The results of the maximum-likelihood classification in the form of classified images are shown in Figure 8.

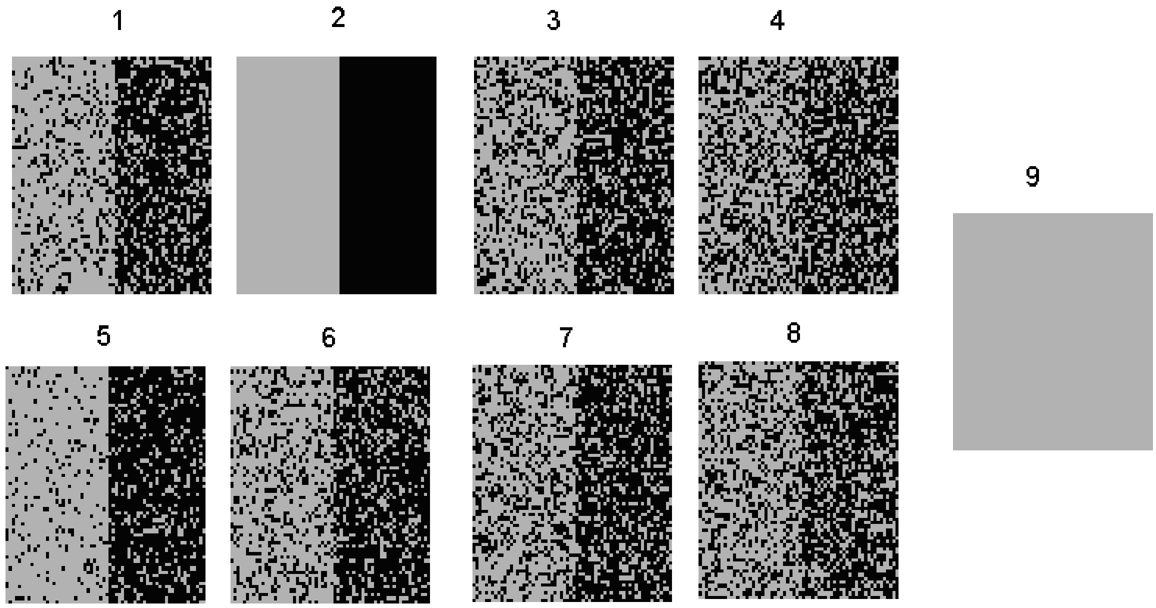

Figure 9. MLH results for various spectral overlaps presented in Table 3 (64×64 pixels).

As it is expected model based image analysis finds the exact place of the edge for approximately all of the cases (with an exception for the case 9). In the case nine, model-based image analysis has failed because of the full radiometric overlap. For this evidences are not true and are very similar to each other then the algorithm cannot find correct edge place. Then we can conclude that using proper knowledge in a constructive manner would help effectively to overcome the classical problems with the standard maximum likelihood classification and reduce the effect of the radiometric overlap on the classification results.

3.4. Experiment 4: Effect of the wrong assumption for data distribution

One of the major characteristics of a parametric classification method such as maximum-likelihood is assuming a predefined probability density function. Specially, maximum-likelihood assumes a Gaussian (Normal) distribution for probabilities and based on it performs its decision. However, as Mulder, 1994 describes, it is a doubtful and questionable assumption, which may cause some ambiguities in decision making. In this experiment we examine effect of this assumption on the model based image analysis and maximum-likelihood. We test some situations in which data has another distribution and are classified by maximum-likelihood, assuming that data has a Normal distribution. The experiment was done for different edge lengths and various image sizes.

To do this, we generated an image with two classes, having an edge in the middle of the image. Again this image has three spectral bands, which were generated using the signatures of the classes A and B shown in the Table 4.2. As a result, image generation for the three spectral bands was done twice including a Normal and a Poisson distribution assumptions for data. Indeed we have two data sets, which one of them has a Normal distribution and the other has a Poisson distribution. Since statistical parameter estimations are depended to the number of the samples then we design different cases with different image sizes including: 16×16, 64×32, 128×64 and 256×128 pixels.

Now with equal prior probabilities we performd maximum-likelihood classification as well as MBIA on these 8 data sets (4 of them have Normal distribution and the remaining have Poisson distribution). Therefore, we have generally two cases, one is the case in which data has Normal distribution and are classified with Normal assumption (ideal case) and in another case, data has another distribution (here Poisson) and classified with normal assumption. For the two cases the corresponding overall accuracy (for maximum-likelihood) and estimated parameters (for MBIA) have been presented in the Table 5.

Table 5. The results of the MLH and MBIA for data with Normal and Poisson distribution

CASE	*EDGE LENGTH*	*Normal Assumption*		*Poisson Assumption*	
		Overall accuracy (%) for MLH	*Estimated parameter*	*Overall accuracy (%) for MLH*	*Estimated parameter*
1	16	75	8	64.1	8
2	64	77.7	16	67.3	16
3	128	78.1	32	70	32
4	256	77.3	64	61.5	64

From Table 5 it can be concluded that statistical assumptions behind some classifiers, can have a strong effect on the results of them. In contrast using the available knowledge in the image analysis makes the classifier resistant to the data behavior. This experiment again confirms of using external knowledge in the process of image classification because we don’t have a perfect understanding about the data from the statistical point of view.

3.5. Experiment 5: Prior probability effect in Bayesian design

The simplest way which is used for incorporating the external knowledge in a classifier procedure like maximum likelihood classifier is through the application of prior probabilities. The prior probability is simply an estimate of the proportion of the objects, which will fall into a particular class (Strahler, 1980). Thus, these are a general view of the percentage of the objects existence in the scene. Definition of the priors is an essential aspect of the Bayesian classifiers (e.g. maximum-likelihood), which can affect the classification results significantly.

In the traditional methods priors are the only ways of incorporating the prior knowledge in the classification process. It can be developed to introduce various knowledge sources in the classification and obtain more accurate results. Strahler (1980) showed such an algorithm for using several knowledge sources in the form of priors and stated some useful aspects of the prior probabilities. He mentions three major capabilities of the priors as bellows:

- The incorporation into the classification of prior knowledge concerning the frequencies of output classes, which are expected in the area to be classified,
- The merging of one or more discrete collateral datasets into the classification process through the use of multiple prior probability sets describing the expected class distribution for each combination of collateral variables, and
- The use Time-sequential information in making outcome of a later classification contingent on an earlier classification (Strahler, 1980).

In many real cases there is no idea about the actual fraction of each class in the scene. Hence the prior often are assumed to be equal and in fact there are no benefits from them into the classification (Susaki et al., 2000).

However the definition of the prior probabilities values is an essential issue, which affects our results directly. Since we have designed the MBIA on the basis of the Bayesian rule, the priors also can influence the results. Therefore, one of the main goals of this experiment is to investigate the sensitivity of the traditional maximum likelihood and knowledge based image analysis approach to the prior probabilities.

Often it is said that because of the insufficient a priori information, the priors are assumed to be equal (Susaki et al., 2000), but if there is sufficient information about the objects in the scene, how we must define the prior probabilities. It seems that if we have exact values for objects priors then we must introduce them into the classification procedure to obtain more accurate results. This is not as simple as stated above, because although the overall accuracy may be increased but we will lose the entire shape of the small classes in the favor of the classes which have larger prior probability.

For example, consider the task of finding roads in a forested area, where the proportion of the forest pixels (say 99%) is used as prior probability for the class forest, leaving 1% for the road. In the result, forest may be assigned to all image pixels, giving the user a useless map with an overall accuracy of 99% in case the user is interested in the road class. If the priors are not considered (e.g. equal priors), user can expect some forest pixels to be classified as road, but at least most of the road pixels will be found, as well. The user has to decide which of the classified road pixels are really class road but this is probably easy, when looking at the spatial arrangement of these pixels. For our experiment we generated an image with size 64×32 pixels with the ground truth of Figure 4.6. We performed the maximum-likelihood classification with various prior probabilities for the two classes which varies from 0 for the class A (then 1 for the class B) to 1 for the class A (0 for the class B), with step 0.1. The overall accuracies of these different cases are presented in the Table 6.

The true case is related to the equal prior probability for the classes (case 6), which gives the best overall accuracy. In this experiment the two classes have the equal priors. The assumption of the equality of the priors did not disturb the overall accuracy. MBIA also finds the true edge place for this case. Table 6, however, shows that the overall accuracy of the maximum likelihood classifier varies by changing the prior probabilities. Among 11 cases, using external knowledge by mean of MBIA the stability of the procedure was kept (for the 5 cases).

For investigation of the small size object class, we assumed an image that is the same as the previous image but its edge is in the column number 3. Thus, the ratio of area class A to class B is 3/32= 0.093 ≈ 0.1. In this case the exact priors are 0.1 and 0.9 that give the best overall accuracy in the maximum-likelihood i.e., 92.1% (see Table 7).

However, if we consider this case, the resulted segmented image shows that the class A is lost and reconstructing it in a post processing analysis is impossible (Figure 10). In the case (6) that we assumed equal priors the overall accuracy suddenly has been very low relative to the exact priors. The overall accuracy from 92.1% for the true priors changes to the 76.3% for the case that priors are equal. Therefore, we have lost about 16% of overall accuracy for the results. Having a look at the Figure 10 shows that in the case 6 (equal priors), two classes are more distinguishable, than the case 2 (i.e. applying the exact priors). An interesting exception in Table 6 is the result of the MBIA, which could not give the exact result in the case of the true priors. It may be referred to an important aspect of the data viz radiometric overlaps, which it has a major influence on the result of the classification.

Table 6. Effect of the prior probabilities on the MLH overall accuracy and MBIA parameter estimation (true edge is in the column 16 for the image with size 64×32 pixels).

Case	*Prior Probability (Class A)*	*Prior Probability (Class B)*	*Overall Accuracy (%)*	*Estimated parameter*
1	0	1	50	1
2	0.1	0.9	60	1
3	0.2	0.8	68.3	1
4	0.3	0.7	73.4	16
5	0.4	0.6	76.5	16

6	0.5	0.5	77.7	16
7	0.6	0.4	76.4	16
8	0.7	0.3	74.1	16
9	0.8	0.2	70.2	32
10	0.9	0.1	64	32
11	1	0	50	32

Table 7. Effect of the prior probabilities on the MLH overall accuracy and MBIA (true edge is in the column number 3).

Case	*PRIOR PROBABILITY (CLASS A)*	*PRIOR PROBABILITY (CLASS B)*	*OVERALL ACCURACY*	*Estimated parameter*
1	0	1	90.6	1
2	0.1	0.9	92.1	1
3	0.2	0.8	91.2	1
4	0.3	0.7	88.3	3
5	0.4	0.6	82.8	3
6	0.5	0.5	76.3	3
7	0.6	0.4	68	3
8	0.7	0.3	60.2	3
9	0.8	0.2	50	32
10	0.9	0.1	36.2	32
11	1	0	9.4	32

However, with the equal prior probability assumption MBIA unlike the maximum-likelihood classification finds the exact edge place. From the Tables 6 and 7 it can be concluded that model based image analysis can give the accurate results with equal prior probabilities. Then it has no sensitivity to equal prior probability assumption, and we can compensate the errors, which may be introduced in the results by equality assumption by means of the using external knowledge.

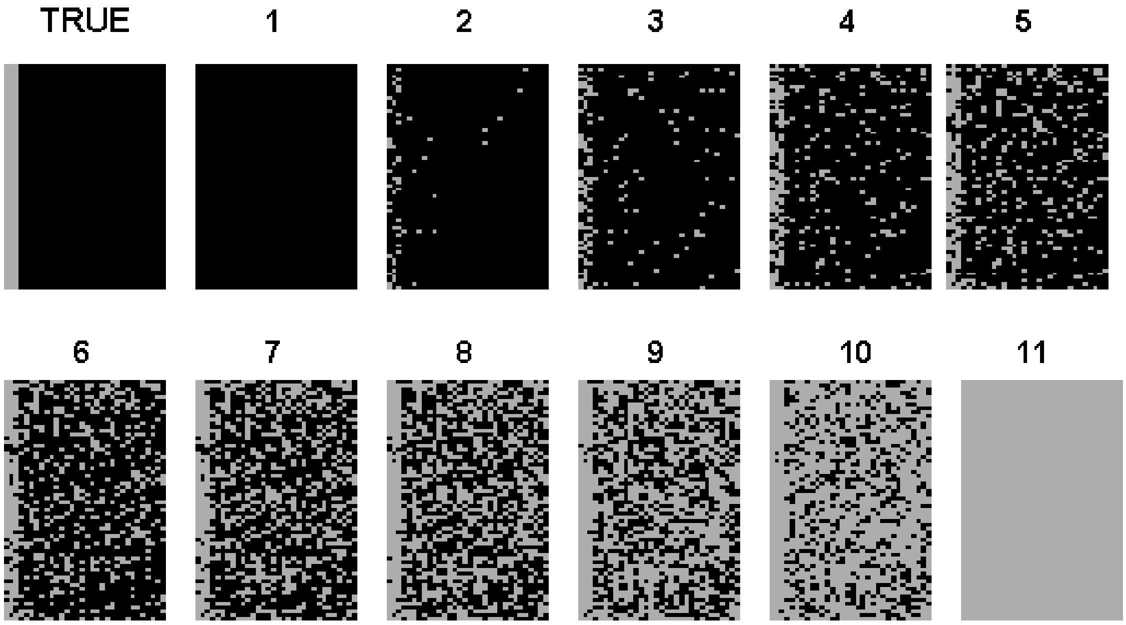

Figure 10. MLH results with various priorsparameters (true edge is in column 3; image size 64×32)

Therefore, with these considerations we can ignore the priors (equality assumption is the same as ignoring the priors) and then introduce our knowledge about the objects in the form of geometric hypothesis. Indeed in the case of MBIA the calculation of the priors for several objects are not required, which is a multi-aspect, and time-consuming work and we can be sure that there is no effect of using this. Hence, we have strong reasons to use equal prior probabilities for parameter estimation (Mulder, 1994).

4. Conclusion

In this paper we discussed various errors, which may be in the remote sensing data and traditional classification methods. Errors may be caused from the similar spectral characteristics of objects or from the atmosphere or sensors. In order to overcome these errors, several methods have been developed which many of them are on the basis of using external knowledge. Hence they use the external knowledge in various forms to improve the classification results.

Model Based Image Analysis (MBIA) also is the novel method that deals with the modeling the remote sensing processes. Using geometric hypothesis and radiometric likelihood, a flexible method is developed, for which various aspects of the remote sensing system (errors and knowledge) can be considered. From the presented experiments in this paper, we can conclude that MBIA is a stable, flexible and reliable method for information extraction from remotely sensed images.

The results confirm that we must acquire all the possible and useful knowledge and make use of them, of course, in an optimum manner. A more limited search space (with considering the completeness of the model) can give good performance of the MBIA and leads to the better inference of the scene, with less error. It was also shown that with increasing the number of parameters, this method still gives good results relative to the Maximum-likelihood classification. For the future work, we would examine the performance of these two approaches for the real case and, of course, with more than two land cover classes.

One difficulty of the model based image analysis in this experiment is the large search space of parameters. To avoid this problem we must limit the number of parameters and search space dimensions. This would be possible by using additional knowledge as constraints. Of course, from the geometry point of view model based approach compared to the Maximum-likelihood method is sound and can give obviously, the better results for real applications. If we merge the semi noisy segments after the maximum likelihood results and even obtain similar results compared to the

MBIA, it will be clear that the complexity of the MBIA is much less than the complexity of the maximum-likelihood classification. A good assessment of this can be found in Abkar and Mulder, 1996.

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