TRANSFERABILITY OF KNOWLEDGE-BASED CLASSIFICATION RULES

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ABSTRACT:

Because of the rising complexity of high resolution imagery, object-based classification methods are becoming more suitable for land cover classifications and acquisition of GIS data than traditional pixel-based classification methods. Object-based classification requires a preliminary segmentation of the image and the application of knowledge-based rules to classify the image into the desired output classes. Currently the rules for classification are defined again for each image. This is quite time intensive and a major obstacle to the automation of the classification process. One goal of the research reported in this paper is to offer one set of knowledge-based classification rules which is suitable for a specific geographic region and reuse/transfer it to similar images. This paper presents an extensive transferability test of knowledge-based classification rules and results from a base rule set which should be valid in several images. Radiometrically uncorrected IRS pan-sharpened images with a pixel size of 5m of eight test sites in Northern Algeria are used. The results show that the transfer of rule bases is feasible and that it is possible to define a base rule set for a specific geographic region for radiometrically uncorrected images. The achieved accuracies are lower than those of individual classifications but the advantages are the reduction in analysis time and the possibility to semi-automate the data acquisition process.

1. INTRODUCTION

With the availability of high resolution image data, new classification methods are necessary to handle the rising complexity of the images as traditional pixel-based classification methods produced unacceptable results. One of those new methods is object-based classification where the processing units are no longer single pixels but image objects. As a first step the complete image has to be segmented into meaningful areas/segments. The next step is to define a set of knowledge-based classification rules to describe each target class. Those rules can contain spectral, spatial, contextual, and textural information. The final step is to assign each segment to the class that fulfils the rules best. The software eCognition is used for this research.

One of the main problems associated with such a classification technique is the necessity to develop a new set of rules for each new image, which is time consuming and is an obstacle to automation. Therefore, the main objective of this paper is to test the prospects of transferring classification rules to different test sites. Transferability means the reuse of segmentation parameters and knowledge-based classification rules that were defined for one image in other images. This research focuses on the transferability of classification rules.

Few attempts (e.g. Esch et al., 2003; Kressler et al., 2003, Mitri et al., 2002) have been made in that direction. It is reported, that classification rule bases were successfully transferred to other images but that adaptation of some rules was necessary. But it is not clear what kind of rules are used in the rule base and which properties are stable in different images. Stable means that an image object property characterises a feature class in several images ideally with the same value range. Quantitative evaluation is also missing in most publications.

In the publication of de Kok and Wever (2002) it is stated that texture is a stable feature and suited to extract built-up areas in very large data sets.

This paper starts with a short overview of the object-based classification concept and a relatively new segmentation algorithm (Multiresolution Segmentation). After specification of the test sites, the practical investigations about transferability of rule sets are presented and results are discussed. At the end of this paper a summary and a conclusion including an outlook are given.

2. OBJECT-BASED CLASSIFICATION

Object-based classification starts by segmenting the image into meaningful objects. The resulting image objects “know” their neighbours and they are subject to the succeeding classification. The classification process is controlled by a knowledge-base that describes the properties of the desired feature classes as fuzzy membership functions. Object-based classification allows the user to take not only spectral properties into account during classification, but also shape, texture, and context information. Arbitrary data like existing GIS layers or digital surface models (DSM) can easily be integrated and used as supportive a priori information in the classification process. For example, Hofmann (2001) used high-resolution IKONOS data in combination with additional elevation information to detect buildings and roads. Object-based classification is also suitable for radar images. For example, Corr et al. (2003) used object-based classification for the production of urban mapping data from interferometric polarimetric synthetic aperture radar (SAR) data.

2.1 Multiresolution Segmentation

The object-based image analysis software eCognition offers a relatively new segmentation technique called *Multiresolution*

Segmentation (MS). The segmentation algorithm is a bottom-up region-merging technique. MS starts by considering each pixel as a separate object. Subsequently, adjacent pairs of image objects are merged to form bigger segments. The merging decision is based on local homogeneity criterion, describing the similarity between adjacent image objects. The pair of image objects with the smallest increase in the defined criterion is merged. The process terminates when the smallest increase of homogeneity exceeds a user-defined threshold. Therefore a higher threshold will allow more merging and consequently bigger objects, and vice versa. The homogeneity criterion is a combination of colour (spectral values) and shape properties (a combination of smoothness and compactness). Applying different thresholds and colour/shape combinations, the user is able to create a hierarchical network of image objects which is necessary to extract different types of objects (area and linear objects) because they require varied segmentation parameters (eCognition User Guide, 2004). Darwish et al. (2003) report about a research work about finding optimum segmentation parameters. Up till now, finding the optimum segmentation parameters is a trial and error process which is usually carried out by experienced analysts.

As already mentioned MS is a region-merging algorithm which depends strongly on the heterogeneity of the image data and on local contrasts. Therefore the image content may influence the transferability of segmentation parameters. The segmentation result of transferred segmentation parameters to another image of the same sensor in a similar geographic region can be evaluated visually or by evaluating the classification result which is based on the segmentation. A comparison of average image object sizes between different images could also serve as an indicator for the transferability of segmentation parameters.

2.2 Knowledge-base

Following image segmentation, the next step is describing the output classes. This is achieved using a knowledge-base (*Class hierarchy*) which defines the properties of the classes to be extracted. Each class description is composed of fuzzy expressions (*Membership functions*) that include logical operations and hierarchical class descriptions. These descriptions may include not only spectral properties but also shape and size characteristics, context, and texture information. Within this class hierarchy it is possible to inherit image object properties from a super-class to a sub-class and also to group classes semantically.

3. TEST SITES

3.1 Image Data

In this study, images from the Indian Remote Sensing Satellite (IRS) are used. The three multispectral bands green, red, and Near infrared (NIR) were merged with the panchromatic band to produce a pan-sharpened image with a pixel size of 5m. The images are not radiometrically corrected. The test sites belong to two geographic regions in Algeria. The first is the coastal region (Northern part of the country) and the second is the desert region (four test sites in each region). The image contents comprise built-up areas, agricultural land, different kinds of vegetation, desert areas, irrigated fields, several water bodies (sea, lake, river), and lines of communication like roads. The distance between the most western and most eastern two test sites in the coast region is approximately 600km. Table 1 and 2 list the used images with their dates of acquisitions and extents. The dates of acquisition spread over nine months (coast) and two years (desert). However it has to be noted that the images in the desert region were all taken in December.

Table 1: Test Sites Coast

Test Site	**Mosta-ganem**	**Algiers**	**Jijel**	**Mandoura**
Date of acquisi-tion	25.11.1999	30.1.2000	11.3.2000	14.8.2000
Extent [km x km]	11 x 10	38 x 19	17 x 10	7 x 6

Table 2: Test Sites Desert

Test Site	**Hassi-El-Frid**	**Northeast of Ouargla**	**Ouargla**	**N'Goussa**
Date of acquisi-tion	25.12.1998	6.12.1998	19.12.2000	19.12.2000
Extent [km x km]	7 x 10	12 x 15	21 x 16	8 x 5

3.2 Output Classes and Evaluation

The output classes comprise four base classes (water, built-up, non built up, and roads). There is no ground truth nor adequate reference data available for Algeria. Therefore visual interpretations of the images are used as reference data.

The evaluation of the classification is done using two assessment tools, Error Matrix (EM) and Kappa statistic values (K). While the former reports three values: Producers Accuracy (PA), Users Accuracy (UA) and Overall Accuracy (OA), the later reports a single K value for each class and an Overall Kappa value (OK). More detailed information about accuracy assessment from remotely sensed images can be found in Congalton and Green (1999).

4. PRACTICAL INVESTIGATIONS

Practical investigations in this research have been carried out in two steps. The objective of the first (transferability test) is to come up with a number of potential classification rules for specific feature classes and test their transferability to other images of each geographic region. The objective of the second step (base rule set) is to analyse the above mentioned classification rules to define a set of rules that is stable and transferable and achieves the highest possible classification accuracies.

4.1 Transferability test

After the definition of segmentation parameters, classification rules were set-up for each test site. Following the classification of each image accuracy assessment was performed. Within each of the geographic regions, the sets of classification rules of each image were transferred to the other three images. The classification results were evaluated after applying the transferred sets and also after adapting (adjusting existing rules -changing image object property values- and if necessary add new rules or feature classes specific for an image) the transferred sets to the new image.

Resulting from this transferability test, there are a number of potential classification rules for specific feature classes and the knowledge which rules were transferable to other images of each geographic region.

4.2 Base rule set

Further investigations deal with the question: which image object properties are transferable or in other words which properties are stable in different images? Therefore potential object properties which resulted from the transferability test (section 4.1) were compared in all test sites of the geographic region coast to come up with a set of knowledge-based classification rules. For this comparison, the four images of the coast region were combined into one big image. Then each of the potential object properties was displayed in eCognition and the ranges used in the initial classification were tested to find if applicable in all images or not. If not, different ranges were tested until either a good range of values is found or the property considered as unsuitable.

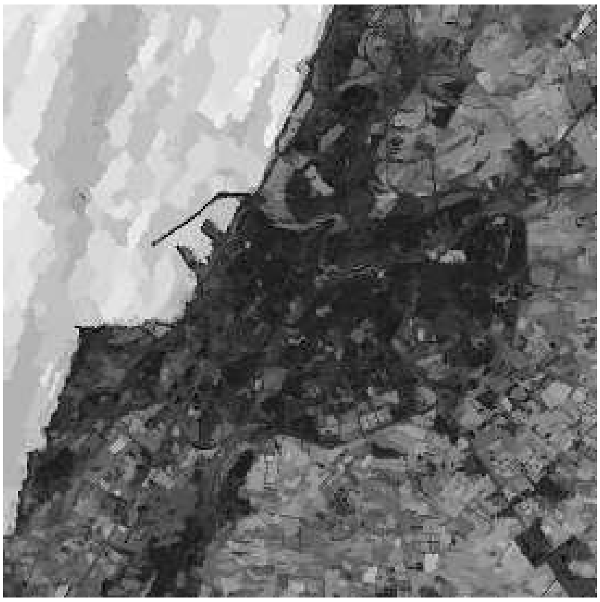

Figure 1: Texture property of Mostaganem

Figure 2: Texture property of Jijel

Figure 1 and 2 show an example of an examined image object property (Grey Level Co-Occurrence Matrix -GLCM- Homogeneity in the NIR channel (Haralick 1973)). The images are displayed in grey values. Dark coloured image objects posses a small value whereas brighter segments have a high value for this texture property. From the figures, it is clear that this texture property has similar values for the built-up areas of Mostaganem and Jijel. It is also visible that using solely this property is not sufficient to classify built-up areas because other features like quarry and bush land also fulfil it.

All other potential properties were analysed in the same manner to produce the base rule set for coast (Table 3). In this set, non built-up areas which comprise different kinds of vegetation like agricultural land and forest, are classified using the Normalized Difference Vegetation Index (NDVI) and the GLCM Variance in NIR. Similar textural and spectral properties characterize the class built-up. The rules for the linear classes roads and river contain shape properties like length to width, ratio and density (the area covered by the image object divided by its radius which describes the compactness of an image object). Water is defined by the Ratio NIR (the NIR mean value of an image object divided by the sum of all spectral channel mean values). Lake and sea are child classes from water so that they inherit the property Ratio NIR from water. The feature lake is classified using shape properties area and length and sea is characterised by the Ratio NIR like the parent class water.

The resulting so called base rule set which contains spectral, texture, and shape properties was applied to all the test sites in the coast region and accuracy assessment was performed.

Table 3: Base rule set for Coast

Class	Property	Range
Non-Built up	NDVI	> 0
	GLCM Variance NIR	0 - 11
Roads	Length/ Width	> 6
	Density	< 0.9
Water	Ratio NIR	> 0.26
Lake (child of water)	Area	> 6500
	Length	< 310
Sea (child of water)	Ratio NIR	< 0.19
Built-up	GLCM ASM NIR	< 0.002
	Mean Green	> 90
	GLCM Homog. NIR	< 0.15
	GLCM Contrast Red	> 70
River	Mean NIR	25 - 50
	Length/ Width	> 3

5. RESULTS AND DISCUSSION

5.1 Transferability test

Table 4 lists the average results of the accuracy assessment of the four test sites in the two geographic regions coast and desert (classification of four base classes water, built-up, non built-up, and roads). The original classification results from the rule base which was developed for the specific image. The transferred classification is produced applying one rule base to the other test sites without making any changes and the adapted one is with adjustments to the new test site. The original classification accuracies with 89% for Coast and Desert are higher than for the transferred and adapted classification results. The results show that adaptation of the rule base increases the accuracy to an acceptable level.

Table 4: Accuracy Assessment of original, transferred, and adapted classification (four base classes)

	Coast			Desert		
	Original	Transferred	Adapted	Original	Transferred	Adapted
Overall Accuracy	89 %	74 %	78 %	89 %	82 %	86 %
Overall Kappa	0.83	0.57	0.65	0.66	0.27	0.56

In addition to the classification of the four base classes, a more detailed classification was performed. Dependant on the image content, the class water for example was divided into sea, lake, and river and built-up into high- and low-density built-up. The detailed classifications comprise up to eight feature classes. Comparing the OA of the base and detailed classification, as expected, it is clear that the base classifications achieve equal or higher accuracies.

Analysing individual feature classes indicates similar accuracies of the transferred and adapted classification for the class water. Therefore it can be assumed that water is transferable. Adaptation of the rule base results in an increase of the quality for the classes built-up and non built-up. There is no clear trend for the class roads. In the coast region, the adapted roads are worse than the transferred and vice versa for the desert region. The dependency of the image characteristics can be clarified especially with roads: Broad, paved roads are more easy to extract than narrow, dirt tracks which are built from the surrounding material.

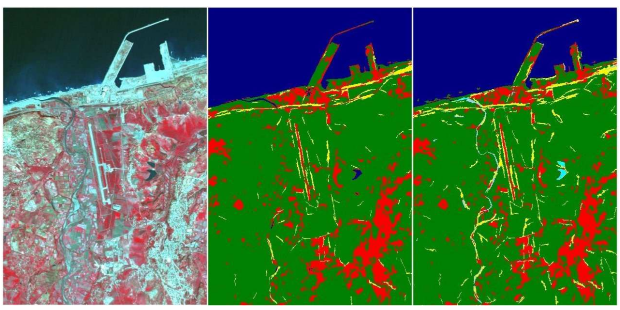

Figure 3: left: IRS image Jijel, centre: transferred, right: adapted classification result

Figure 3 shows a classification example of the transferability test. On the left hand side is a subset from the IRS image of the test site Jijel. In the center the classification result from the transferred rule base from the test site Mostaganem is displayed and to the right the adapted result. The transferred result contains only one water class (dark blue). The sea and one lake are correctly classified as water, most of the river is not classified. After adapting the rule base both lakes (bright blue) are correctly classified by taking into account context information (neighborhood to other than water classes) and most of the river is extracted. Classified built-up areas are displayed in red, non built-up in green, and roads in yellow.

Table 5: Accuracy Assessment transfer of the rule base from Mostaganem to Jijel (four base classes)

	Mostagenam → Jijel		
	Original Jijel	Transferred	Adapted
Overall Accuracy	87 %	80 %	87 %
Overall Kappa	0.8	0.69	0.8

The accuracy assessment results from the transfer of the rule base from Mostaganem to Jijel (four base classes) are listed in Table 5. The OA, as well as the OK of the transferred classification, are lower than the original classification of Jijel and the adapted result. By adapting the rule base an improvement can be achieved which produces an OA and OK equal to the original classification.

5.2 Base rule set

Similar to the transferability test (section 4.1), three accuracy assessment steps were performed for each image. The first is the accuracy of the transferred base rule set, the second is from the adapted rule set and the third is the accuracy from the classification with added rules to the base rule set. Figure 4 is an example of the calculated accuracies and it reports the OK for the four test sites, in addition to the accuracy of the original, individual classifications (four base classes). For example, figure 4 shows that the OK for Jijel is 0.61 and it increases to reach 0.65 and 0.7 after the adapting and addition phases, respectively. The figure also shows that the average OK of the transferred rule set is 0.67, 0.69 for the adapted rule sets and 0.71 for the classifications with the added rules. In spite of the higher accuracies achieved after adding new rules, it still falls below the average OK (0.83) for the original classifications. The OA shows similar results (Figure 5). The average OA for the transferred base rules set is 79% and it increases to 82% after adding new rules. Again, this is less then the average accuracy (89%) of the original classifications.

The average Kappa values of the coast classification results for individual feature classes are presented in figure 6. Except for the class water, the original Kappa values have the best accuracy. For water the accuracies of the transferred, adapted, and original classifications are nearly the same. The accuracies of the transferred classifications of the classes non built-up and built-up are considerable lower than the original Kappa values but with an average of 0.7 and 0.55, respectively, they are higher than those of roads. This linear feature class delivers the worst results with a maximum Kappa value of 0.39 for the transferred and added rules classification but the individual classification are not much higher with a Kappa of 0.42. Roads are quite difficult to extract because of their special geometry (narrow, elongated) and the image resolution of 5m is not sufficient to achieve better results with object-based classification.

Analysing all of the above results, it can be noticed that the adaptation and adding of new rules to the base rule set do not improve the classification result significantly, in contrast to the transferability test where the adaptation of the rule base enhanced the accuracy considerably. The main difference between these two studies lies in the used object properties. The rule bases in the transferability test were optimised to one certain image and then transferred. In contrast, the base rule set comprises object properties which should be stable in several images of one specific geographical region. Therefore adaptation brings only small improvement.

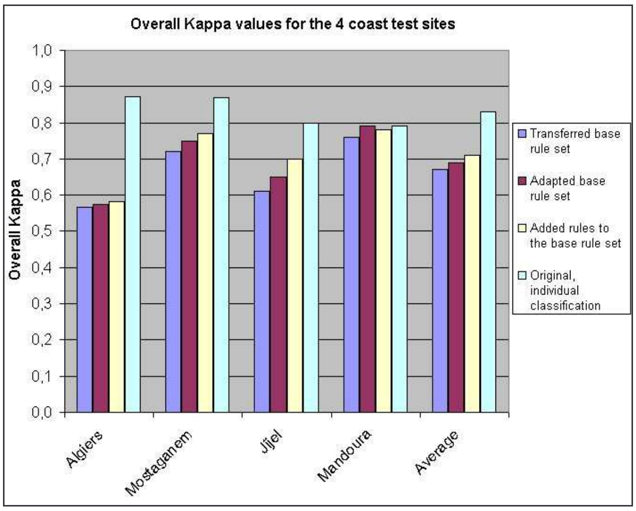

Figure 4: Overall Kappa values for the 4 test sites Coast (four base classes)

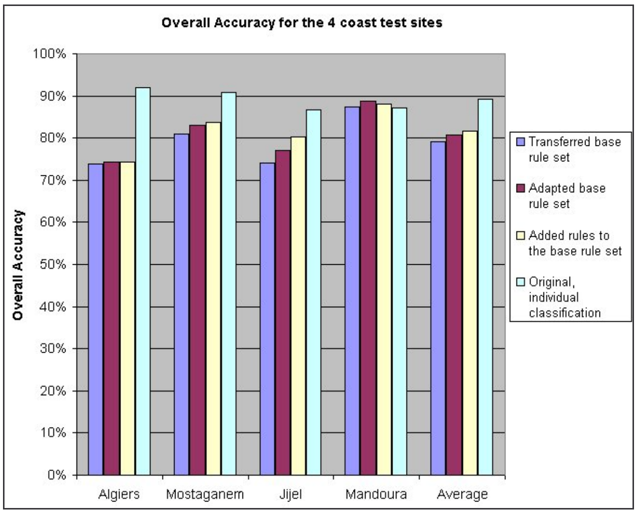

Figure 5: Overall Accuracy for the 4 test sites Coast (four base classes)

Transferring the base rule set to a new test site decreases the OK by 20% and the OA by 11% (four base classes). After adding new rules, the OK decreases by 15% and the OA by 8% in comparison to an individual classification which usually requires much more time. The investigations with the base rule set show the feasibility of transferring knowledge-based classification rules but the gain of automation and time for image classification leads to a certain loss of accuracy.

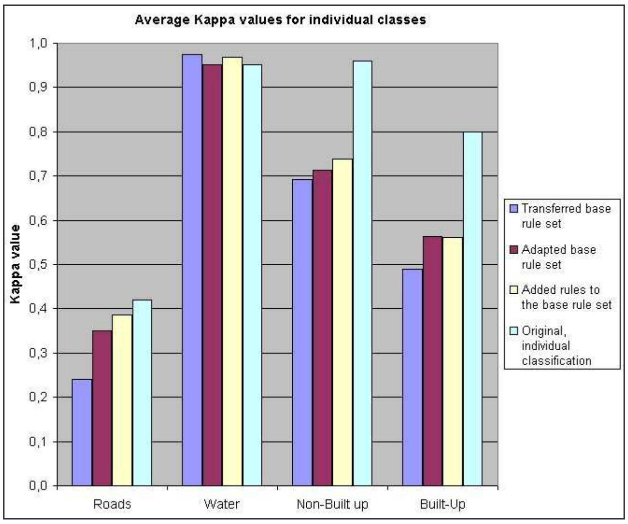

Figure 6: Average Kappa values for the individual classes (coast, four base classes)

5.3 Discussion

When investigating the transferability of classification rules potential influencing factors have to be considered. The following items may influence the transfer of knowledge-based classification rules:

- Date of image acquisition (season, sun elevation)
- Relief (shadow)
- Atmospheric impacts
- Geographic region (occurrence and appearance of objects)

It is possible to decrease the impact of the listed factors. One option could be by limiting the proposed knowledge-base to a specific season and/or to a specific geographic region. In this work the rule base was limited to a specific geographic region. Nevertheless feature classes may have different appearances and new feature classes might appear. Atmospheric impacts and shadows due to the relief can be reduced by applying atmospheric and topographic corrections. Because of unavailable meteorological data radiometrically uncorrected data was used here and it was a challenge to test the transferability of rule bases for this kind of data.

The classification rules can use radiometric, texture, and shape properties of the image objects as well as relations between different image objects. Radiometric properties are strongly influenced by atmospheric impacts, season, and sun elevation. Texture is a more stable feature because it represents the structure of the pixels grey values and not absolute intensity values. Especially for man-made objects like roads shape features play an important role and the investigations with the base rule set show that they are transferable. Descriptions of context between image objects have to be universal to be transferable.

6. SUMMARY AND CONCLUSION

The transferability of classification rule sets for a specific geographic region is a challenging task. Topographic features appear in a broad variety and illumination effects additionally complicate finding stable and transferable properties for image classification. After the introduction of the object-based classification concept in this paper, two kinds of practical investigations about transferability of rule sets were presented. The first is a transferability test which objective is to come up with a number of classification rules for specific feature classes and test their transferability to other images of each geographic region. Following the above mentioned classification rules were analysed to set up a base rule set in a specific geographic region.

The extensive transferability test demonstrated the feasibility and high potential of transferring knowledge-based classification rules to establish a semi-automatic workflow for object extraction with a high level of automation. It can be summarized that when transferring rule bases region specific adaptations are necessary but they can be done in short time. This leads to a clear gain of time in comparison to an individual definition of the rule base for each new image. The classification rules comprise next to spectral mainly texture properties for area features and shape properties for linear features like roads and river. The practical investigations with the base rule set showed also the feasibility to define knowledge-based classification rules valid for one specific geographic region.

The availability of a base rule set brings the following advantages:

- Semi-Automation of the image classification: it is not necessary to define an individual rule set for each new image
- Gain of time
- Cost reduction for data acquisition
- No expert user required

The above advantages come at the expense of the classification accuracy which is less than the accuracy of an individual definition of the rule set.

There should be further investigations in an operational data acquisition environment to assess the time necessary for postprocessing the results from individual and from transferred classifications. It is believed that the gain of time resulting from the transfer of a rule base will be much higher than potential additional work because of the lower accuracy. Other investigations will deal with the verification of the base rule set in new independent test sites of the same geographic region and the definition of a base rule set for another geographic region, namely desert areas in Algeria.

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