REGION-BASED AND KNOWLEDGE-BASED APPROACHES IN ANALYSING REMOTELY SENSED AND ANCILLARY SPATIAL DATA – EXPERIENCES FROM CASE STUDIES

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ABSTRACT

The present article discusses region-based and knowledge-based approaches for analysis of remotely sensed data by summarizing research conducted in various application areas. Different approaches and methods, e.g. image segmentation and rule-based classification, have been applied and interpretation procedures for map updating, building detection, crop species interpretation and snowmelt monitoring have been developed and tested. Experiences gained from these case studies are discussed in the article and concluded to be promising. Use of region-based instead of pixel-based approaches facilitated interpretation and resulted in classifications of improved thematic accuracy and visual quality. Knowledge-based approaches provided flexible means of combining information from different types of spatial data in the analysis and thus increasing the accuracy of the results. Some subjects requiring further study and development include automation of knowledge acquisition and efficient integration of existing map and GIS data at various stages of image analysis.

1. INTRODUCTION

Automatic interpretation and classification of remotely sensed images is a research subject that has attracted wide attention during recent decades. Many different approaches have been tested and advanced algorithms developed, but the problem has proved to be a very demanding one to solve. Accuracy levels high enough for operational applications, e.g. in mapping or environmental monitoring, are not easy to achieve with completely automatic methods.

Pixel-based spectral classification with techniques such as the maximum likelihood (ML) method (e.g. Richards and Jia, 1999) has become a standard approach in analysis, but since the 1970s research has also been conducted to develop methods that would better resemble the work of a human interpreter (see e.g. Tailor et al., 1986; Argialas and Harlow, 1990). These studies include development of segmentation algorithms and use of spatial, contextual and structural information as well as ancillary data sources and expert knowledge in addition to spectral information. In studies related to automatic object extraction from high-resolution aerial images, approaches developed in the fields of computer vision and image understanding are commonly applied. Model- and knowledge-based methods for extracting buildings and roads have been developed and much progress has been made (see e.g. Gruen et al., 1997). In analysis of satellite imagery with lower spatial resolution, promising results have been obtained by applying segmentation algorithms, using region-based and knowledge-based interpretation procedures and including ancillary data sources in the analysis (see e.g. Kettig and Landgrebe, 1976; Janssen, 1993; Johnsson, 1994). These types of method, however, have not been commonly used in practical work.

During the last few years, interest in image segmentation and alternative classification approaches has been increasing (see e.g. Blaschke et al., 2000; Willhauck, 2000; GeoBIT/GIS, 2001; Hyyppä et al., 2001). It has become evident that traditional pixel-based classification approaches are not sufficient for interpretation of data from new, high-resolution spaceborne and airborne sensors with a pixel size of a few metres or less (see e.g. Hoffmann and Van der Vegt, 2001). At the same time, commercial software packages including tools for segmentation and region-based (or object-oriented) and/or knowledge-based image analysis have become available (Arbonaut, 2001; Definiens Imaging, 2002; ERDAS, 2002). Integration of image analysis and geographical information systems (GIS) has also become an important research topic (Baltsavias and Hahn, 2000). Image data are used to create and update GIS datasets while the existing GIS data are used as prior information in image analysis, and a trend for complete integration of photogrammetry, remote sensing and GIS can be observed (Heipke et al., 2000). Such developments clearly offer new possibilities for image analysis and require new approaches to be used in interpretation.

At the Finnish Geodetic Institute (FGI), research to develop region-based and knowledge-based approaches for analysis of remotely sensed data, mainly satellite images, was begun in the early 1990s (Soikkonen, 1993). Since then, the research has been continued and application areas under study have included map updating (Matikainen et al., 1997), building detection (Matikainen et al., 2001), crop species interpretation (Matikainen et al., 1998) and snowmelt monitoring (Matikainen et al., 1999; 2002). Remotely sensed data applied in the studies have ranged from laser-scanning and aerial image data with a pixel size of 30 cm x 30 cm to National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data with a pixel size of 1 km x 1 km. Common to all the case studies has been a region-based and/or knowledge-based approach applied in the analysis. The goal of the present article is to summarize the research conducted in various application areas by concentrating on two general aspects: 1) how interpretation of remotely sensed data can be improved by interpreting regions instead of single pixels and 2) how interpretation of remotely sensed data can be improved by using additional data sources and knowledge. Details on data, methods and results of the case studies can be found in the earlier publications.

2. SEGMENTATION AND REGION-BASED ANALYSIS

2.1 General

When interpreting regions instead of single pixels, it becomes possible to use properties of the regions in the analysis. Attributes such as size, shape and texture of the regions and contextual information related to relationships between neighbouring regions can be used. In addition, it can be expected that classification on the basis of spectral information is more reliable when it is based on the mean values of homogeneous regions instead of single pixel values. The classification process also becomes faster as the number of objects to be classified decreases.

Regions needed in the analysis can be obtained by using an image segmentation or partitioning algorithm (e.g. Kettig and Landgrebe, 1976). Hundreds of segmentation algorithms have been presented in the literature (Argialas and Harlow, 1990). Some of them have been developed for special applications, others are more general. Segmentation can be used as a preprocessing operation before further analysis and interpretation of the imagery, but approaches combining segmentation and interpretation stages have also been developed (e.g. Gorte, 1998). In the case studies discussed in this article, segmentation has been used as a preprocessing operation to provide preliminary regions for further analysis. Image segmentation was applied in the map-updating (Section 2.2) and building-detection (Section 2.3) studies.

As an alternative for image-derived segments, existing map data can be used to define regions for interpretation (e.g. Janssen, 1993; Johnsson, 1994). This may be the best approach if regions of a permanent nature are analysed using remotely sensed data. This approach was applied in the crop species interpretation and snowmelt-monitoring studies (Section 2.4).

The third alternative to obtain regions for interpretation is to combine image-derived segments with regions obtained from maps (e.g. Ait Belaid et al., 1989; Janssen, 1993). This is the best approach if useful map data exist but several spectral classes can occur within a map region or changes in region boundaries can be expected. Such an approach was tested in the map-updating study as will be described in Section 2.2.

2.2 Segmentation of Landsat TM images for map updating

A segmentation method based on hierarchical region merging (Beaulieu and Goldberg, 1989) was implemented and used in a map-updating study (Matikainen et al., 1997). An initial partition into very homogeneous regions is produced by using a simple region-growing algorithm. The main idea of the segmentation method is then to merge segments gradually according to their similarity. Segmentation is an iterative optimization process in which the two most similar neighbouring segments in the image are merged at every iteration. The number of segments decreases by one at every iteration, and by varying the stopping point of merging, segmentation results with various numbers of details are obtained. These results together form a hierarchical structure in which the segments on an upper level consist of several segments on a lower level. Handling of this structure was not implemented at the FGI, but it could be advantageous for further analysis of the image (Beaulieu and Goldberg, 1989). The segmentation method was implemented such that existing map data can be used as a mask in the segmentation. Areas belonging to various land-use classes can be segmented separately from each other. Finally the results are combined to obtain one segmented image. By this means, segment boundaries become compatible with the existing map data and the spatial accuracy of the final interpretation results will improve, assuming that the spatial accuracy of the existing map data is good.

The segmentation method was tested in two study areas: Lohja in southern Finland and Zhong Shan in southern China. A Landsat Thematic Mapper (TM) image from both study areas was available. In the Lohja area, the image was filtered to reduce noise before segmentation, and masks derived from an old land-use map were used to perform segmentation separately for water, forest, field and urban areas. The boundaries of the segments thus became compatible with the old map data, which facilitated further analysis and improved the appearance of the final interpretation results. On the other hand, displacements between the image and map caused some distortions in the segmentation result. In the Zhong Shan area, filtering and old map data were not used. A segmentation result from Lohja is presented in Figure 1; to allow evaluation of the quality of image segmentation, this is a result produced without the aid of map data. A merging criterion minimizing the increase in overall pixel variance around the segment means at every iteration (Beaulieu and Goldberg, 1989) was used.

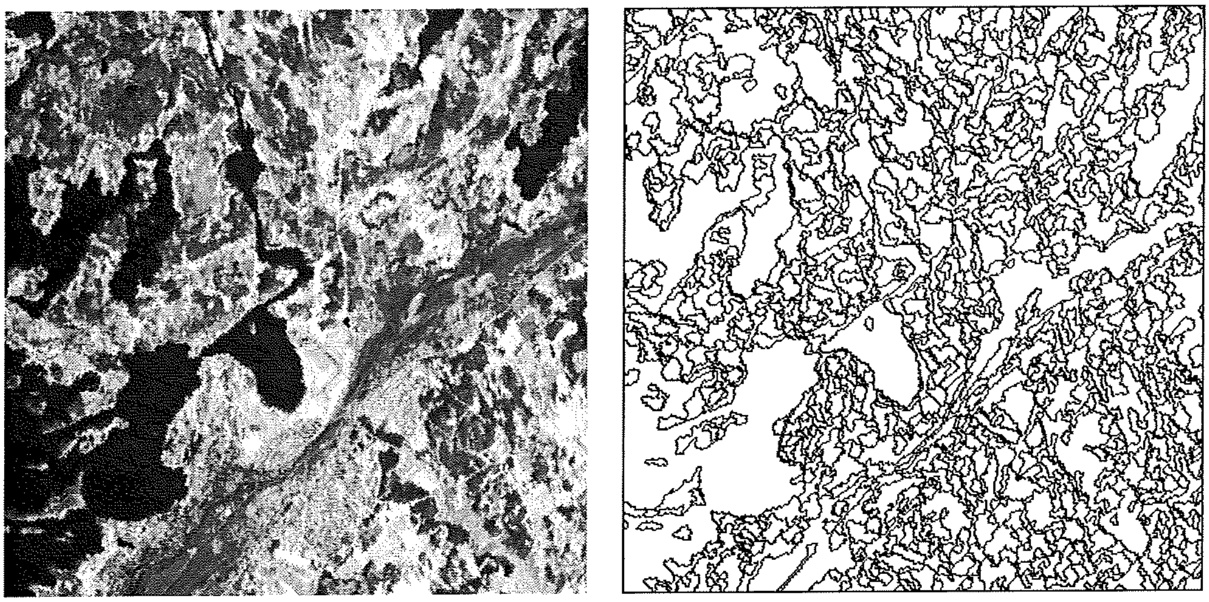

Figure 1. Landsat TM image (left, channel 4) and segmentation result (right) from the Lohja study area. The size of the area is 10 km x 10 km. Landsat TM © ESA, 1989, Eurimage/Novosat Ltd.

As a first step in interpretation, a supervised ML classification was performed for the segmented images by using the mean values of the segments in classification. Training areas for 56 spectral classes in the Lohja area and 33 in the Zhong Shan area were defined interactively on the screen. Training statistics were calculated from the original image data, not from filtered and segmented images. A pixel-based classification using the same training statistics was also performed. A comparison of the accuracy between segment-based and pixel-based classification is shown in Table 2. Results from the segment-based ML classification were used in a further rule-based classification step together with old map data to obtain updated land-use classifications for the study areas (see Section 3.2).

2.3 Segmentation of laser-scanning data for building detection

In another case study related to image segmentation, the goal was to automatically detect buildings from laser-scanning and aerial colour image data (Matikainen et al., 2001). The study area was located in Otaniemi, Espoo, about 10 km from the city of Helsinki. In this study, the segmentation tool of the eCognition software (Definiens, 2000) was used. This segmentation algorithm (Baatz and Schäpe, 2000) is also based on bottom-up region merging and an optimization procedure, but the decision strategy for finding regions for merging differs from that applied in the algorithm of Beaulieu and Goldberg (1989). Common to Beaulieu and Goldberg (1989) is the feasibility for producing a hierarchical sequence of segmentation results with objects of varying sizes. In eCognition these results form an image object hierarchy that can be used in further analysis. Results obtained by segmenting a digital surface model (DSM) derived from the laser-scanning data are shown in Figure 2. A heterogeneity criterion minimizing colour (in this case corresponds to height) heterogeneity of the segments was used.

A simple two-staged classification procedure was developed to classify segments into three classes: building, tree, ground surface. At first, segment was classified as 'tree or building' if the difference in the mean height between the segment and the segment with the lowest mean height within a square neighbourhood was over a given threshold value. The best classification result for the study area was obtained by using a window size of 40 m x 40 m and a threshold value of 3 m.

After this, any segment classified as 'tree or building' was classified as 'building' if the mean value of the segment in the red channel of the aerial image was over a threshold value. This rule was selected after examining distributions of different features in the two classes. High accuracy was achieved, although it must be noted that the test area was small and the same manually defined reference classification for the segments was used both for finding good features and threshold values for classification and for accuracy testing. Interpretation accuracies for the three classes were: buildings 94%, trees 97%, ground surface 97%; the total accuracy was 97%. The classification result is shown in Figure 2.

Figure 2. Segmentation (left) and classification (right) results from Otaniemi. In the segmentation result, segment boundaries are shown on the laser-derived DSM. In the classification result, buildings are shown in light grey, trees in dark grey and ground surface as black.

2.4 Using map information to define regions for interpretation

2.4.1 Crop species interpretation

A knowledge-based method for crop species interpretation was developed and tested using European Remote Sensing Satellite (ERS) Synthetic Aperture Radar (SAR) and SPOT (Satellite Pour l'Observation de la Terre) data together with information on crop species grown in the study area in two successive years (Matikainen et al., 1998). The study area was located near the town of Seinäjoki in western Finland. The approach was region-based and regions for the analysis were taken from a parcel map digitized from aerial orthophotos. A region-based approach is a natural choice for crop species interpretation because one crop species normally covers the entire parcel. The parcels are relatively stable, and base parcel maps covering the whole of Finland are currently available (base parcels can contain several agricultural parcels that need to be defined separately by digitizing or using image segmentation). Administrative information collected on crop species is also parcel-based. In the case study, SAR images were the main source of data, and due to speckle in the images a region-based classification approach was useful. As a first step in interpretation, a parcel-based ML classification of the SAR images was performed. The accuracy of the results is presented in Table 3. A further rule-based classification step will be described in Section 3.3.

2.4.2 Snowmelt monitoring

In a case study related to operational snowmelt monitoring in Finland, a method was developed to estimate drainage area-based snow-cover percentages from NOAA AVHRR images (Matikainen et al., 1999; 2002). A region-based approach was selected because recognizing partially snow-covered areas using single pixels would be difficult. Due to varying land cover in the 1 km x 1 km resolution, small geometric inaccuracies and date-to-date variations in the data can cause reflectance changes that cannot be distinguished from changes caused by changing snow conditions on a pixel-by-pixel basis. When the area under analysis consists of several pixels, interpretation can be based on movement of the histogram (or change in the mean value of the area) as snowmelt proceeds. The histogram is not likely to change decisively as long as snow conditions remain unchanged. Results from a drainage area-based interpretation of snow coverage are also well suited for further use in hydrological models that use drainage areas as basic calculation units. Inside drainage areas, the snow-cover percentage is first estimated separately for each main land-cover class to account for the different rate of melting in different classes. A drainage-area map and a land-cover map are thus used in addition to the satellite images. The study area included the whole of Finland. Snow-cover percentages estimated from the images were compared with ground measurements and appeared to be satisfactory.

3. KNOWLEDGE-BASED INTERPRETATION

3.1 General

In many applications, different types of spatial data from the study area are available and better results could be obtained if these data were included in the automatic image analysis process, in a manner somewhat similar to what a human interpreter would do. Typical examples of such ancillary data sources are different types of maps and GIS datasets, digital elevation models and other types of data with known spatial location. Using standard image classification algorithms it is difficult to include different types of data in the analysis, but with a knowledge-based approach the problem can be handled (see e.g. Srinivasan and Richards, 1990; Richards and Jia, 1999).

The basic parts of a knowledge-based image analysis system are a knowledge base and an inference engine (e.g. Richards and Jia, 1999). The knowledge base contains knowledge needed to solve the classification problem, typically rules defined by a human expert. The task of the inference engine is to make inferences on the basis of the data and the knowledge base, e.g. to define the land-use class for a segment under analysis using a satellite image, an old land-use map and rules stored in the knowledge base. An important part of the decision-making process is an uncertainty-handling mechanism.

Various knowledge-based approaches have been developed for different image analysis tasks, ranging from relatively simple classification methods to more complex object-extraction systems (e.g. Srinivasan and Richards, 1990; Wilkinson and Mégier, 1990; Kontoes et al., 1993; Baraldi and Parmiggiani, 1994; Johnsson, 1994; De Gunst, 1996; Tönjes et al., 1999). Approaches used in the case studies discussed in this article have been relatively simple methods dealing with class assignment for segments or pixels based on spectral information or a preliminary classification result and ancillary spatial data sources.

In studies related to map updating (Section 3.2) and crop species interpretation (Section 3.3) rule-based interpretation software developed at the FGI was used. The software was originally implemented by Soikkonen (1993) and later developed further. The interpretation program is capable of interpreting image pixels or segments by using rules and attributes derived from various data sources, e.g. satellite images, classification results and raster maps. When interpreting a pixel or segment, the rules assign belief to various classes or sets of classes in a class hierarchy, depending on the values of the attributes for the current segment or pixel. It is also possible to use initial belief values that are based on class probabilities calculated in a previous classification. All the belief values are combined by using Dempster's rule of combination, which is part of the Dempster-Shafer theory of evidence (Shafer, 1976). An algorithm presented by Shafer and Logan (1987) is used in the calculation. This algorithm was developed for cases in which hypotheses (e.g. land-use classes) form a hierarchy and each piece of evidence assigns belief to only one hypothesis or complement of a hypothesis in the hierarchy. In the snowmelt-monitoring study (Section 3.4), simple categorical and fuzzy rules implemented in Matlab (MathWorks, Inc.) were used for the classification task.

3.2 Map updating

In the map-updating study, a rule-based classification was performed to combine information derived from Landsat TM images (see Section 2.2) with that obtained from existing topographic maps in order to define the final class for each segment (Lohja, Zhong Shan) or pixel (Zhong Shan). The goal was to take the information content of the old map into account, instead of defining a completely new land-use classification using the image data alone. Some land-use classes, such as water and urban areas, are normally very stable, and depending on the nature of the area under study, some land-use changes are more typical than others. Topographic information in the form of digital elevation data can also provide useful information. In the Zhong Shan study area, for example, fields and water areas are typically situated in a flat and low area, while most forested areas and quarries are found at higher elevations in mountainous areas. If properly applied, this type of knowledge can be useful in correcting misclassifications and solving uncertainties resulting from spectral classification.

To find useful classification rules for the study areas, the preliminary ML classification results, old land-use maps and digital elevation data were analysed using up-to-date reference data. Cooccurrence matrices were formed and used as an aid in defining rules and belief values for interpretation. Some rules were based on our knowledge of the areas. Examples of rules used in the Zhong Shan area are shown in Table 1. In the Lohja area, the pre-classification results were included in the rule-based classification by using class probabilities obtained from the ML classification.

Table 1. Examples of interpretation rules used in the Zhong Shan area.

Condition	Action
If land use is water	Confirm water area 0.9999
If land use is field	Confirm field 0.60
If land use is field	Confirm water area 0.10
If land use is field	Confirm urban area 0.15
If land use is field	Confirm open area 0.15
If ML class is garden	Confirm garden 0.65
If ML class is garden	Confirm forest 0.20
If ML class is garden	Confirm rice 0.10
If height < 10 m	Disconfirm forest 0.90
If height > 25 m and ML class is open	Confirm open 0.25
If height > 25 m and ML class is open	Confirm quarry 0.50
If class is urban area and any neighbour is forest and none of the neighbours is rice and none of the neighbours is garden and none of the neighbours is open	Confirm quarry 0.9999

As a final step in the interpretation, a postclassification based on neighbourhood relationships was performed. New segments were created by connecting all neighbouring pixels belonging to the same class, and the postclassification rules were applied to these areas. Due to the complex relationships between areas, only one useful rule could be defined for the Zhong Shan area (the last rule in Table 1) and three for the Lohja area. The accuracies of the final interpretation results are shown in Table 2, together with accuracies of the pixel-based and segment-based ML classifications. The final results shown for Zhong Shan were obtained by applying ML classification for segments, rule-based classification for pixels and postclassification for new segments. The rule-based classification step had to be applied for pixels due to the numerous very narrow canals in the study area. These canals were not clearly visible in the Landsat TM image and to include them in the final result (from the old map), a pixel-based classification step was necessary. It is also worth noting that many errors in interpretation resulted from problems in the data, such as the low spatial resolution of the satellite images compared with the 1:50 000 maps to be updated and displacements between different data sources.

Table 2. Accuracy for pixel-based ML classification, segment-based ML classification and final result from rule-based classification in the map-updating study. Number of points in the reference datasets is shown in brackets.

	Pixel-based ML classification / Segment-based ML classification / Final result after rule-based classification (%)					
	Water	Field	Forest	Urban	Open	Total
Lohja	(28 633 p.)	(25 408 p.)	(72 622 p.)	(11 438 p.)	(5352 p.)	(143 453 p.)
Interpretation accuracy	84 / 87 / 96	74 / 74 / 90	78 / 87 / 87	44 / 63 / 71	29 / 27 / 26	
Object accuracy	98 / 98 / 95	64 / 73 / 76	85 / 85 / 90	43 / 52 / 73	14 / 35 / 41	
Mean accuracy	**90 / 92 / 95**	**68 / 73 / 82**	**82 / 86 / 89**	**43 / 57 / 72**	**19 / 31 / 32**	
Total accuracy						**74 / 81 / 86**
Zhong Shan	(11 p.)	(61 p.)	(16 p.)	(17 p.)	(25 p.)	(130 p.)
Interpretation accuracy	36 / 64 / 64	79 / 85 / 87	69 / 56 / 88	35 / 76 / 82	72 / 68 / 68	
Object accuracy	67 / 100 / 100	77 / 80 / 90	69 / 90 / 93	29 / 46 / 48	72 / 85 / 85	
Mean accuracy	**47 / 78 / 78**	**78 / 83 / 88**	**69 / 69 / 90**	**32 / 58 / 61**	**72 / 76 / 76**	
Total accuracy						**67 / 75 / 81**

3.3 Crop species interpretation

In the crop species interpretation study, a rule-based classification relatively similar to that used in map updating was performed. Crop species information from the previous year, a SPOT multispectral (XS) image from early spring and results from parcel-based ML classification of four ERS SAR images obtained during the growing season were used in interpretation.

Information on crop species grown in the parcels during the previous year is valuable in interpretation because it makes it possible to use knowledge of crop rotations (e.g. Janssen, 1993). For example, some species are not normally grown in the same field in two successive years, but for some other species this is a typical practice. Mean values of the parcels in the near-infrared channel of the SPOT image were used to assign belief to spring crops, rye (the only winter crop in the dataset) and grassland. In an image from early spring, these classes can be distinguished from each other with relative accuracy. A cooccurrence matrix, general knowledge of agricultural practice and histograms were used in defining rules and belief values to be applied for the crop species information and SPOT data. Finally, results from the ML classification of SAR images were included by using class probabilities as belief values.

The accuracy of the results is shown in Table 3. SAR images were included in chronological order, i.e. if one image was used, it was the first one obtained. It is worth noting that no training parcels were defined for rye in the ML classification and the accuracy of this class in the ML classification results was thus 0%. In rule definition two rye parcels were used, but none of the three rye parcels used in the accuracy estimation could be detected in interpretation.

Table 3. Accuracy for parcel-based ML classification and final result from rule-based classification in the crop species interpretation study. Number of parcels in the reference dataset is shown in brackets.

Number of SAR images used	**Parcel-based ML classification / Final result after rule-based classification Mean accuracy of the classes and total accuracy of the classification (%)**					
	Grassland (37 p.)	Rye (3 p.)	Oats (29 p.)	Barley (70 p.)	Turnip rape (6 p.)	Total (145 p.)
1	44 / 74	0 / 0	0 / 11	45 / 73	12 / 0	**33 / 63**
2	66 / 80	0 / 0	45 / 43	40 / 74	28 / 33	**47 / 68**
3	70 / 84	0 / 0	73 / 78	62 / 82	33 / 31	**63 / 79**
4	75 / 81	0 / 0	78 / 83	75 / 87	35 / 60	**72 / 83**

3.4 Snowmelt monitoring

The third study related to knowledge-based interpretation concerned development of a method for snowmelt monitoring (Matikainen et al., 1999). Input data for interpretation included NOAA AVHRR images, results from ERS SAR image interpretation (obtained as presented by Koskinen et al., 1997) and temperature, precipitation and snow depth measurements from weather stations. The idea of the method is to produce snow maps daily during the melting season by using all the data sources available for that day. Information obtained from the various data sources is included in the interpretation by using simple rules the purpose of which is to resemble inferences a human interpreter might use; e.g. the higher the mean air temperature, the more probable it is that the existing snow cover is wet. The method was developed and tested by applying it to 1 km x 1 km pixels. The main study area was located in the Kemijoki River drainage area in northern Finland. Weather data for each pixel were obtained from the closest weather station.

A simple two-level class hierarchy with classes snow-free ground, snow, dry snow and wet snow was defined, and rules were formed to give support to these classes. Existing data were analysed e.g. by using image histograms to find rules and threshold values for interpretation. The final support value for each class was obtained as the sum of the support values. In addition to the snow maps, reliability maps and melting intensity maps were produced. The reliability category (1-5) for each pixel was obtained by comparing support values given to different classes. The melting intensity value (0-20) for each pixel was derived linearly from the mean air temperature data. Cloudiness and problems in ERS SAR image acquisition hampered development and testing of the method, but results obtained agreed relatively well with water level measurements in the Kemijoki River drainage area. Use of weather data in addition to satellite images allowed continuous monitoring of the melting process.

4. DISCUSSION AND CONCLUSIONS

4.1 Results of the case studies

In the case studies (Table 4), image-derived segments or regions obtained from maps could be successfully used as basic regions for image interpretation. Segmentation results obtained both in the map-updating and building-detection studies were satisfactory. In crop species interpretation, the parcel map provided a natural basis for combined analysis of images and parcel-based information on crop species. In the snowmelt-monitoring study, using a drainage area-based approach allowed estimation of snow-cover percentages, which on a pixel-by-pixel basis would have been difficult. Combination of existing map data with image segmentation was tested in the map-updating study. Image-derived segments became compatible with the map data, which facilitated further interpretation and improved the appearance of the final interpretation results. On the other hand, displacements between the image and map caused some distortions in the segmentation result.

In all case studies, region-based classifications resulted in homogeneous regions much like in a map or in a manually produced interpretation. Table 2 shows that in the map-updating study use of segmentation as a preprocessing step improved the accuracy of the ML classification of Landsat TM images by 7-8 percentage units compared with pixel-based classification. In the case studies, interpretation was mainly based on spectral and thematic attributes of the regions. Shape and size attributes were not used, mainly due to the relatively low spatial resolution of image data in most of the studies and nature of the applications (crop species interpretation, snowmelt monitoring). In the map-updating study, some rules related to neighbourhood relationships between segments were used in the postclassification stage. In the building-detection study, use of the region-based approach allowed a simple classification rule based on heights of neighbouring segments to be used. High accuracy was achieved by using this rule and an additional rule based on spectral characteristics of the segments. In this case study, shape attributes of the segments could also be useful. In general it is likely that importance of spatial and contextual information increases as the spatial resolution of the data increases (see e.g. GeoBIT/GIS, 2001).

Use of different types of ancillary data sources to improve classification in a knowledge-based approach was tested in three case studies and the results were promising. In the map-updating study, use of the old land-use map and digital elevation data improved the total accuracy by 5-6 percentage units, compared with segment-based ML classification of Landsat TM images (in the Zhong Shan area, rule-based classification was applied for pixels). Accuracy increase compared with pixel-based ML classification without ancillary data was 12 percentage units in the Lohja area and 14 percentage units in the Zhong Shan area. In crop species interpretation, improvement in rule-based classification compared with ML classification of four ERS SAR images was 11 percentage units (Table 3). Ancillary data sources in this study included a SPOT image and crop species information from the previous year. When using ML classification of 1-3 SAR images with the other data sources, improvements in the rule-based classification stage were 30, 21 and 16 percentage units, respectively. In the snowmelt-monitoring study, accuracy testing could not be performed, but use of weather data in addition to satellite images allowed continuous monitoring of the melting process. The multisource input data were also useful in defining reliability estimates for the results.

Use of knowledge-based approaches in the case studies allowed flexible combination of information from various sources. Thematic maps as well as digital elevation data and weather observations could be exploited in the analysis in addition to image data. This would have been difficult using traditional statistical classification approaches. Hierarchical class structures were used and support could thus be given not only to individual classes but also to groups of classes, depending on the information content of each data source. In rule definition, cooccurrence matrices and image histograms were exploited, but in some cases it also proved useful to define rules that were based on general knowledge of the subject or visual evaluation of the data and results. This was easy to realize because a knowledge-based approach was applied.

Table 4. Summary of the case studies and main results related to region-based and knowledge-based interpretation.

Case studies and main processing steps	**Main results** (p.u. = percentage units)
MAP UPDATING (Study areas: Lohja in southern Finland and Zhong Shan in southern China)	

Region-based analysis
• Segmentation of a Landsat TM image
  • Lohja: with the aid of old map data
  • Zhong Shan: without the aid of map data
• ML classification of the segments
• ML classification of pixels for comparison
	
	⇒ Total accuracy of the segment-based ML classification: Lohja 81%, Zhong Shan 75%
	⇒ Increase in ML classification accuracy compared with pixel-based classification: Lohja 7 p.u., Zhong Shan 8 p.u.
	⇒ Improvement in visual quality of the results compared with pixel-based classification

Knowledge-based analysis
• Rule-based classification of the segments (Lohja) or pixels (Zhong Shan)
  • Input: Result of the segment-based ML classification, old land-use map, digital elevation data
  • Postclassification based on neighbourhood relationships
	
	⇒ Total accuracy: Lohja 86%, Zhong Shan 81%
	⇒ Increase in accuracy compared with segment-based ML classification: Lohja 5 p.u., Zhong Shan 6 p.u.

BUILDING DETECTION (Study area: Otaniemi near the city of Helsinki)	
Region-based analysis • Segmentation of laser-scanning data • Classification of the segments using a thresholding approach • Input: laser-scanning data, aerial colour image	 ⇒ Total accuracy 97% ⇒ Good visual quality of the results ⇒ A simple classification rule based on segment heights could be used
CROP SPECIES INTERPRETATION (Study area: near the town of Seinäjoki in western Finland)	
Region-based analysis • Parcels from a parcel map digitized from aerial orthophotos • ML classification of the parcels • Input: 1-4 ERS SAR images	 ⇒ Total accuracy 72% (4 SAR images) ⇒ Good visual quality of the results ⇒ Parcels provided a natural basis for crop species interpretation ⇒ Region-based approach was useful in classifying SAR images with speckle
Knowledge-based analysis • Rule-based classification of the parcels • Input: Result of the ML classification, SPOT image, crop species information from the previous year	 ⇒ Total accuracy 83% (4 SAR images) ⇒ Increase in accuracy compared with ML classification 11-30 p.u., depending on the number of SAR images used in ML classification
SNOWMELT MONITORING (a) (Study area: the whole of Finland)	
Region-based analysis • Drainage areas and land-cover classes from map • Estimation of snow-cover percentages for the drainage areas • Input: NOAA AVHRR images	 ⇒ Satisfactory agreement with ground measurements ⇒ Good visual quality of the results ⇒ Region-based approach was useful in estimating snow-cover percentages from AVHRR images ⇒ Drainage area is a feasible unit for further use of the results in hydrological models
SNOWMELT MONITORING (b) (Study area: Kemijoki River drainage area in northern Finland)	
Knowledge-based analysis • 1 km x 1 km pixels • Rule-based classification • Input: NOAA AVHRR images, results from ERS SAR image interpretation, weather data	 ⇒ Use of weather data made continuous monitoring of the melting process possible ⇒ Multisource input data were useful in defining reliability estimates for the results

4.2 Further development

Experiences gained from the case studies have also brought out subjects that would need further study and development. One of these is definition of rules and support values, which is a laborious and demanding task. Use of rules defined by human experts is a common approach applied in knowledge-based systems, but statistical approaches for evidence acquisition have also been developed (see e.g. Peddle, 1995). We believe that this type of analytical method should be used whenever possible, because it will make interpretation more automatic and objective as well as easier to apply for new study areas and data sources. Automatic tools for knowledge acquisition should thus be developed. The methodology used for evidence combination should also be further studied. In the rule-based classification program developed at the FGI, Dempster's rule for the hierarchical case is used, which means that each rule is treated as a distinct, independent piece of evidence. This was not necessarily the best approach for combining the type of statistically derived support values used in the case studies. Experiences from the snowmelt-monitoring study suggest that in some cases even a very simple evidence combination scheme may work if carefully planned. Use of existing map and GIS data in various stages of the analysis is another important subject for further study and development. Simple approaches for including existing map data in segmentation and interpretation were tested, but further studies on the subject are needed. It is important to realize the integration in such a way that image analysis and change detection are supported and results with high geometric and thematic quality are obtained. Interrelationships between segmentation and interpretation stages should also be developed; improvement of the segments in the interpretation stage should be possible. Finally, integration of region-based and knowledge-based interpretation methods with existing GIS and image processing software is needed to make the methods feasible for operational work.

Experiences from the case studies show that region-based and knowledge-based approaches in the analysis of remotely sensed data are promising. We expect that approaches of this type, which combine information available from GIS and other data sources with different types of imagery and try to form and analyse meaningful regions, are needed to achieve real progress in automatic analysis of remotely sensed data. This conclusion is also supported by current trends and developments in the field (see e.g. Baltsavias and Hahn, 2000; GeoBIT/GIS, 2001).

ACKNOWLEDGEMENTS

Several persons and institutes have participated in the research projects within which the case studies were conducted and provided data for the studies. The authors wish to thank them all. Special thanks to Jochen Grandell, who participated in the snowmelt-monitoring study and to Professor Juha Hyyppä, who guided the building-detection study and gave useful comments on the manuscript.

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