ANALYSIS OF IMAGE OBJECTS FROM VHR IMAGERY FOR FOREST GIS UPDATING IN THE BAVARIAN ALPS

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ABSTRACT

Pixel based analysis deals with the three basic features of a single pixel; Position Size and Value. The important spatial context of the pixel is used in filter operations, where the output value is assigned to the central pixel. In the middle of the 70th, Landgrebe (1976) tried to register the important spatial context of the pixels (the software ECHO), assuming that a local pixel-group was representing a specific spectral distribution of the local land-cover class. Such analysis could only be successful when the problems with segmentation algorithms were solved. Cross and Mason (1988) continued this work, using quad tree segmentation techniques. In the work of Molenaar (1990), the basics of mathematics similarity between raster surface description and vector surface representations were shown. As this similarity was obvious, the powerful use of the SQL analysis of the database with raster (image) objects would be feasible.
In the later work of Gorte (1998A), the importance of the quadtree segmentation image output in combination with a table link showed how GIS objects and raster (image) objects could be treated in the same way inside one database. Gorte pointed out the curious lack of attention in the standard literature on the potential of segmentation for remote sensing of earth observation. He also pointed out the pre-advantage of the remote sensing and GIS synergy which was considerably assisted with object based image analysis. The late 90 shows a remarkable increase of interest in the remote sensing community for advanced segmentation techniques and the possibilities of advanced SQL applications among image objects. In Munich the Delphi2 e-Cognition team has been concentrated since 1995 on the development of an image analysis software which combines an advanced segmentation technique with a database of image objects, which are linked through an hierarchical network. Their philosophy is based upon a Fractal Net Evolution` concept derived from the ideas of Dr. Binnig. Fractal Net Evolution is an efficient method for the description of complex semantics within largely self-organizing and dynamic networks. It combines insights into the fractal semantic of the world with object orientation. (Baatz, 1999).

The forestry service in Bavaria has been aware that the new generation of satellite sensors could offer an alternative to the standard photogrammetric analysis of the state forest areas. With a predefined object , `The Forest Stand` and a standard forest map scale of 1:10.000, the imagery with 10 meter resolution up to 1 meter panchromatic data could offer enough detail to allow the extraction of important forest parameters from Very High Resolution data (VHR, 5 meter resolution and more). Previous studies from Kenneweg et.al. (1991) showed the difficulties of standard procedures of spectral analysis in forestry using VHR data from aerial platforms. Although successful in Landsat type of imagery, it became clear that the 1:10.000 map scale and the new generation of Satellites like Ikonos and Quickbird needed another approach The imagery could not only be used in visual interpretation, but the advantage of the digital data would be taken into account in an automatic analysis procedure. The utilization of the crucial spatial context of raster imagery were already shown in Neural network analysis and Wavelet transformations. Object based analysis opened up another way, were the filter size of the moving window defining the context became irrelevant and more important, allowed a construction of the database with spectral as well as spatial and topological features of the pixel population, making up the image objects.
Experiments in the forest of the Bavarian Alps have shown, that automatic analysis is possible with 1 meter panchromatic data in combination with multispectral bands (deKok,1999). Important forest parameters, such as stand closure, deterioration, erosion and species composition can be derived automatically from such type of data in the difficult terrain of the Bavarian Alps. The database of Delphi2 eCognition merges image and GIS analysis, allowing any kind of imagery being integrated with the existing forest GIS. In this way making it possible to analyze this data, using fuzzy logic decision rules. The synergy of remote sensing and GIS, offers a good basis to assist the planning and decision process needed to maintain a stable mountainous forest so it can continue to play a multifunctional role in protection, production and recreation in the Bavarian Alps.

1 CLASSIFICATION

Classification decisions are grouping sets of unique ‘objects’ into classes, which members share a common feature. In standard classification the ‘objects’ are single pixels and these pixels have 3 attributes; Value, Position and Size. The pixels line up in arrays, making up an ‘image’. A digital image contains only implicit information about the objects in the scene. Based upon object models, it is possible to discern individual entities in a seemingly unstructured collection of pixels. In a *per –field* analysis or ‘pixel in polygon’ analysis, pixel information is already linked to a spatial database build up in a digitizing session. In the spatial database, besides the explicit information, there is still a huge amount of implicit information available (Sester,2000).

1.1 Traditional

Normally, image analysis takes place in 3 basic domains of image-data and deals with *Image space, Spectral space* and *Feature space* (Landgrebe, 1999). There is a common held conception that the main processing tasks in remote sensing are concerned with the labeling of each pixel, but this is not necessarily so (Hinton, 1999). Non pixel-based classifications are well known in radar analysis. Analyzing such data therefore means offering the geometric resolution of the image to achieve a signature characteristic of the surface. This is not a real problem if objects of interest are formed by a group of pixels (>30). Standard radar analysis focus on the use of GIS derived polygon data to calculate statistics inside a surface. Most of the time these polygons are made by an operator and therefore time consuming. Classical image analysis tools for *per-pixel* analysis are focuses on decisions in *Feature space* (Richards 1992), a statistical domain where the advantages of computer calculation abilities are used. Traditionally, two fundamental decision steps for pixels have to be taken:

1. Labeling a pixel to define it’s object class, using it’s unique spectral values in feature space and/or the values of it’s predefined neighborhood (using filter operators).
2. Grouping the labeled pixels to an image object, using the topological structure of the labeled neighbors, a GIS operation (after Molenaar, 1990).

1.2 Object oriented

Object based analysis uses the ‘image object’ or ‘local pixel group’ as a basis. Thus, the image object can take the spatial context of the pixel population into account. The image object can be considered as the 4th attribute of a pixel, answering the question of :’ to *which (spatial) pixel population does this pixel belong* ‘. Consequently, the registration of the neighborhood results in a construction of a database. In the software eCognition, this database registration is advanced and user friendly and therefore fit for use in this study. The database in eCognition describes the image object in the context of the semantic network. The network is based upon sub-objects and their connection to neighboring objects, which form a super-object on a higher (in this case) hierarchical level. The following shows a way of dealing with these possibilities:

1. An advanced segmentation algorithm is used to select pixels from different raster layers. These pixels are assigned to a local spatial pixel population. This population is called an image object and a constructing takes place of the object topology and registered in a relational database.
2. The different image and GIS layers are connected through their image objects (multi-level segmentation) and their object relationships, thus creating a semantic network, both in their horizontal as well as their vertical neighborhoods.
3. Objects which are similar with respect to an operator-selected feature group are assigned a label, using query functions formalized with fuzzy logic decision rules. A class is a group of objects sharing the same selected features (attributes).
4. Classified neighboring objects are merged to create a knowledge based polygon layer with it’s additional database.

2 SEGMENTATION AND DATABASE OUTPUT

Image segmentation as a ‘basis’ for classification has been around in remote sensing community for quite some time now. Experiments by Kettig and Landgrebe (1976), already showed the weak spots of conventional ‘per point’ approach (*per-pixel*), which lacks the possibility to describe dependencies between adjacent states of natural objects. In ‘*The Extraction and Classification of Homogeneous Objects’* (ECHO, Landgrebe, 1976) the ‘objects’ as a result of the segmentation were mentioned and the important role of tabulated results or type map that should be an output product for a segmentation session is pointed out. The switch from pixel-oriented to table oriented analysis is main focus in data reduction (Haberäcker,1995). Run length encoding and quad-tree structures are widely used in data compression techniques. An extensive use of the tabulated result or more precise a database linked to image objects beyond the registration of pixel arrays in a recoverable format, is a step which seems to be overlooked or at least not used to it’s full extent in many a segmentation algorithm. The application of segmentation algorithms in remote sensing analysis seems

to be out of the main field of image analysis in environmental applications during the 80th and 90th. Meanwhile in industrial applications there was a constant development concerning this issue and the link to fuzzy set theory has been brought to attention as well (Haberäcker, 1995). Although regular appearing in RS literature (Janssen, 1994,Cross, 1984, Gerbrands,1990, Gorte,1995), Gorte (1998A) points out the lack of this subject in standard literature for educational purposes in environmental remote sensing, such as Sabins (1978), Lillesand (1987) and Richards (1992)
In the early studies of Gorte (1995), image segmentation based on quad-trees was used to improve classification results. With an additional table output (Gorte 1998A), a basis for intensive GIS-RS synergy has been made available. Object oriented classification of agricultural parcels has been under study in the work of Janssen (1994). The integration of GIS and remote sensing databases where a hampering factor for his research. Janssen points out the low level database integration of standard software of Arc/info (ESRI) and ERDAS in 1994. Also the segmentation goals in the study of Janssen (1994) focus upon the creation of new vector boundaries. Gorte points out that by register the raster object, in the database analysis, the need for the vector outer boundary disappears (Oral remarks).
With the development of the eCognition software, two basic deficits have been solved since the Janssen (1994) study; A theory for formalizing knowledge in object-based image interpretation is solved with the use of fuzzy logic rules in combination with a semantic network and the highest integration level of one database for raster and vector data has been achieved.

2.1 Segmentation equals classification !?

The study of Flack (1996) gives an insight in the need for contextual information and an increasing use of GIS and RS data, especially where hyper-spectral data as well as VHR data is concerned. Also Flack’s description of segmentation versus classification is made clear in the statement; ‘ *The classification of an entity relies upon the context within which it is embedded. Establishing the context of an entity, however depends on the ability to group like entities, and therefore requires some form of classification. The latter is the segmentation problem’(Flack,1996).* This similarity between segmentation and classification becomes very clear in the work of Schneider (1999). Classifying scene objects per-pixel is a special case of object classification, where the single pixels are the objects (after Schneider, 1999). Flack (1996) notices the general misconception of segmentation, solely seen as a pre-processing step for classification. Also Gorte points out the need for iterative classification-segmentation sessions (Gorte, 1998B). As there is no conceptual difference, it should be noticed that such a per pixel view of classifying scene-objects still holds it’s value for particular digital data, where, from the user point of view, the sensor characteristics depend upon a scale factor in proper relationship with the objects of interest. A multi-layer approach combining different sensor data in both segmented and classified layers are under these considerations a proper way to handle different sensor data as well as GIS layers. Furthermore, Flack’s remarks on the object-based segmentation approach, signalizes a lack of incorporation of proven statistical techniques as well as a less theoretically sound basis. However, the need for hybrid approaches to contextual classification with respect to the consideration of spatial objects is obvious (Flack, 1996). Using object based classification, such as used by the eCognition software, the segmentation part is directly linked to the construction of an image-object database. The resulting map is simply a graphical display of that database. This is similar to any other GIS application. Classification is assigning a label to a set of objects which have a positive response to a condition of a query function. Statistical decisions in feature space are very necessary if attributes are similar and statistical decisions become necessary in the face of huge similarity. Database queries focus-in on a fingerprint-like combinations of attributes of the object set. Including attributes such as spatial context and textural behavior makes this approach reliable. The focus on unique features that are allowed to be correlated, makes query based decisions acceptable as an extension to statistical decisions among independent features. So there is a practical difference between segmentation and classification in the software eCognition, here segmentation is linked to the database construction, classification is a query result from this database.

3 A DESCRIPTION OF DELPHI 2 eCOGNITION, IT’S PHILOSOPHY AND POSSIBILITIES IN IMAGE ANALYSIS.

3.1 The role of the scale factor

Although the origin of the image analysis is still quite dominant in the eCognition software, more and more it is transforming into a spatial analyzer. The analysis tools allow the user to rely on standard thematic map output from GIS and remote sensing, as well as offering a set of tools for data which are preferably not processed using traditional methods. It is not intended to make traditional analysis superfluous, but forces these traditional practices to define the limitations of their scale and object domain. From a remote sensing point of view, traditional multi-spectral methods are bound to a certain sensor resolution at a certain scale level. Landsat type data belong to a 1:50.000 mapping scale in which the role of the maximum likelihood spectral classifier is still powerful. For VHR data, the object based analysis tools using fuzzy logic decision rules is more successful. The thematic maps such as the 50 Meter DTM grid can be analyzed according to traditional Boolean logic as well as the fuzzy logic set available in eCognition. The main focus is the landscape project, build around a set of image and thematic landscape data. The (image-) objects are embedded in a multi-level landscape matrix which allows both an Eco-topological description of the objects as well as a modeling of the chorical dimensions (Leser,1997) of the landscape. The way certain layers are build into the landscape model is very much depending upon the origin of the data-type, such as sensor based mapping, land-surveying point data, administrative boundaries etc. The layered multi-scale landscape description is very much in line with standard GIS. The huge pre advantage of eCognition above standard GIS is the availability of automatic extracted spatial objects available from automatic multi-level segmentation analysis.

3.2 The 'project' in Landscape analysis

Each analysis session starts with the construction of a 'Project'. The user has to define in advance the objects of interest and the thematic layers needed to construct a landscape that is defined through inter-linked 'landscape objects'. These objects represent land cover surfaces and have at least a minimal size and a unique position linked to layer. This exclude point and line objects, these should be defined as surfaces with a minimal dimension. Analyzing a landscape model using 'objects' is partly using modern concepts from cartography as well as object-oriented approaches in computer science, this allows possible confusion (after Molenaar.....). Although introducing new vocabulary is only useful when generally accepted, it fits very well to describe objects from the initial segmentation round in terms of *image object primitives*. After a cycle of classification and segmentation, the resulting output delivers *objects of interest* and the database table output that belongs to it. The introduction of expert knowledge is essential in three different phases of the analysis. The most complicated one is the construction of the semantic network that depends very much upon the sequence of segmentation and the basic spatial objects desired. The second important phase is the definition of classes per object layer. The third step is the construction of the fuzzy logic decision curves for each class. If raw image data needs to be classified, nearest neighbor or fuzzy logic decision rules can be applied for object classification. If required, fuzzy logic decision curves can be constructed on the basis of training areas. If for particular classification, the fuzzy decision curves are known, no training areas are required. To deal with modern developments in image analysis, the following combination applied in the eCognition software package, proved to be a successful one:

- An advanced segmentation algorithm, that is linked to an object oriented database. Through this link, the output of the multi level segmentation is embedded in a hierarchical semantic network.
- One single database for GIS and (satellite) image information to guarantee full synergy.
- Query of the database through fuzzy logic decision curves, allowing the formalization of the expert knowledge.
- Full input format facilities through 'PCI-Geogateway and ASCII,BMP and TIF output facilities, allowing the export of raster based objects with their table link.

4 ACASE STUDY; SELECTED EXAMPLES

To give more insight in the classification procedure with an object hierarchy, several typical examples from a classification session in mountainous forest area have been selected. The imagery used in this case study is similar to actual satellite data and has a direct link to the forest GIS available. The basic object in the forest GIS is the forest stand. This is an area which is defined by homogeneous treatment and therefore an administrative boundary. This condition does not mean that the surface within a forest stand has also a homogeneous spectral/textural response. This problem is widespread in forest GIS and deviates from the *per-field* analysis in agricultural domain such as used in the studies of Janssen (1994) or van Leeuwen (1996) Therefore, at first, the attributes from the GIS layers are important but not the polygon definition. The area descriprion is needed in a further stage of the GIS analysis. (relationship to sub-objects). The resulting objects of interest can be easily integrated as vector data into the forest GIS under ArcInfo/ArcView. However, the strategy is to reach an advanced level of analysis with image objects using the eCognition software package, before continuing further GIS analysis using administrative forest stand boundaries in standard GIS software.

4.1 A GIS synergy with 5 Meter panchromatic and SPOT multi-spectral data

Remote sensing using 5 (to 10) meter panchromatic data and multi-spectral imagery around 20 meters are the major part of the mainstream satellite imagery from past and for coming decades. Landsat, SPOT, MOMS and IRS can be seen as major workhorses and their sensor specifications have been proven to be effective in median mapping scale (1 :100.000 up to 1:50.000). The quality, quantity, temporal availability and familiarity of this data type among remote sensing specialists, assures that new data products are generally compared to standard products from this sensor type. Although the 5 meter panchromatic band in this case study is derived from a mosaic of 15 orthophoto's with 80 cm resolution, the way this data is handled shows very well the possibilities of an object oriented analysis applied to panchromatic data ranging from 5 to 15 meter and multi spectral data from 4 to 30 meters pixel resolution.
The first possibility of introducing expert knowledge is the selection of the different aggregation/segmentation levels.

In this case study 4 layers are defined:

1. A GIS analysis layer.
2. A Remote sensing layer based upon image objects derived from the NDVI and Panchromatic image
3. A Layer with Inventory points derived from the forest GIS.
4. A layer with sub-objects of similar *aspect*, a DTM derivative.

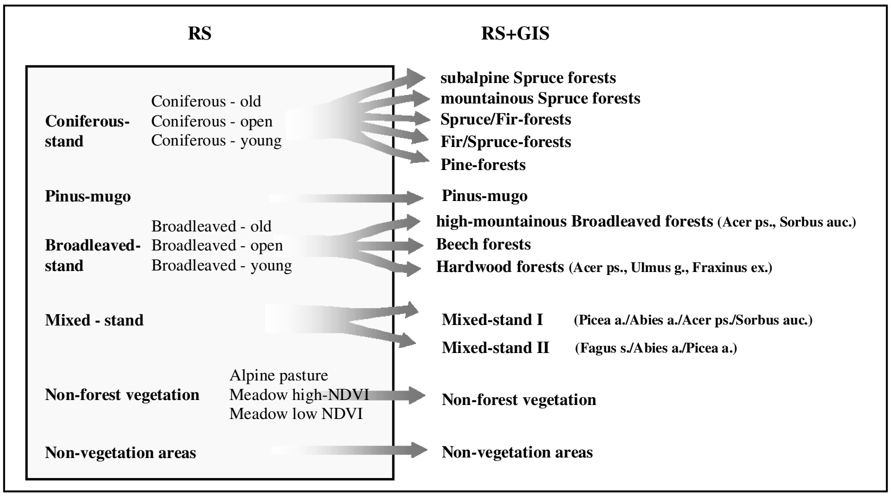

Figure 1, Reclassified remote sensing layer and GIS. The latter using GIS info like height, exposition, forest management map, stand info etc.

Using this particular version, the strategy of modeling is focused upon image objects with homogenous forest cover in layer 2. The sequence of segmentation is layers 2,1,3,4. In layer 2, tolerance parameters are set in such a way, that small gaps around 0.5 Hectare in the forest stands are registered as the smallest single objects. For multi level segmentation, the Panchromatic band receives a weight value of 1, the NDVI of 0.5 and Spot 2, 3 and 4 a weight factor of 0.2. It is important in this study, that weight and tolerance factors are set according to objects of interest and adapted through interactive experiments. The intention is to use layer 2 as a classification layer for pure spectral and textural analysis. The contents of layer 1 is segmented with the same parameters as layer 2. Therefore it is based on identical objects with equal size as layer 2. This layer 1 however will we used to analyze GIS attributes and relies on the classified results of layer 2 (see figure 1) Layer 3 contains inventory points from the forest GIS. They are used in a further GIS analysis. They should be placed in a separate layer to prevent data corruption. Layer 4 contains *aspect*. This layer should respect the outer boundaries of the image objects from layer 2 and should not corrupt point data from layer 3. As features within multi-spectral data and panchromatic data are direct related to the forest stands, the *aspect* should not disturb the shape and size of these image objects, because in the further GIS analysis, there is a need to work with absolute aspect values, therefore this separate layer is required. For other GIS information such as height, the absolute value is of minor importance as for this attribute the range is required.

4.2 Object classification: A selected object within it's sub-class.

The remote sensing part is fully concentrated on the 2nd layer and uses spectral and textural attributes. There is a need for training area's to define the decision curves. The class hierarchy is listed in figure 1.

The panchromatic band is highly correlated with the red and green band from SPOT. The considerations of including the mean value of the panchromatic band should be made clear beforehand as the use of the panchromatic brightness is ambivalent in many image scenes. In imagery with simple classes (forest, non-forest) it could be useful from a practical point of view. In alpine environment, terrain induced illumination has a huge impact on panchromatic brightness values and therefore this study only uses derivatives from the panchromatic band such as standard deviation per object as a textural feature and a combination with relative brightness of an object towards the entire scene. For certain classes, the textural features are very important. The standard deviation per object of the panchromatic band is such a textural measurement. For a typical example, figure 2 shows the separation of *coniferous-old* versus *coniferous-open* in the feature' standard deviation of the panchromatic band'. The curve for *coniferous-open* (on the right) is edited in favor of *coniferous-old* (on the left).

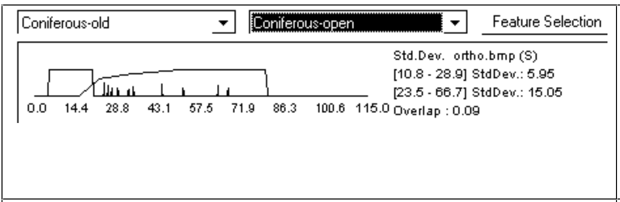

Figure 2. Box classifier for Coniferous-old, adapted box classifier for coniferous-open (user defined).

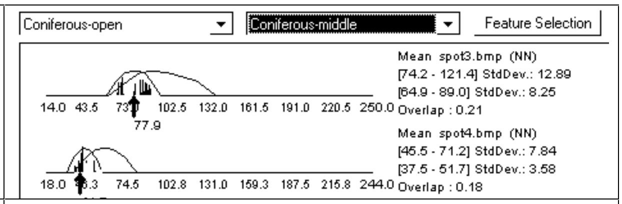

Figure 3. Fuzzy logic decision curves for SPOT-4 Mean values of band 3 and 4.

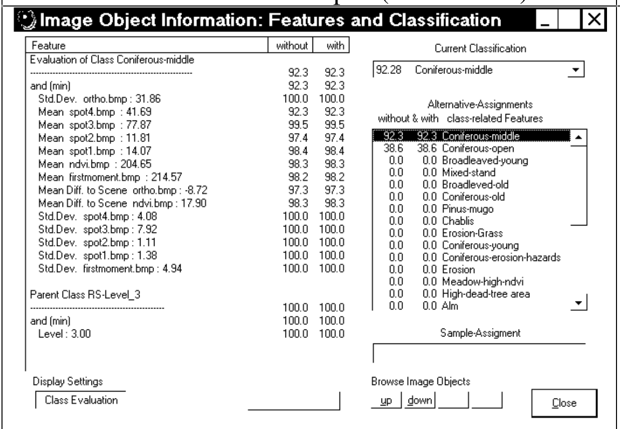

Figure 4. A selected object is correctly classified as coniferous-middle, second possibility is membership of coniferous-open with 38.6 %.

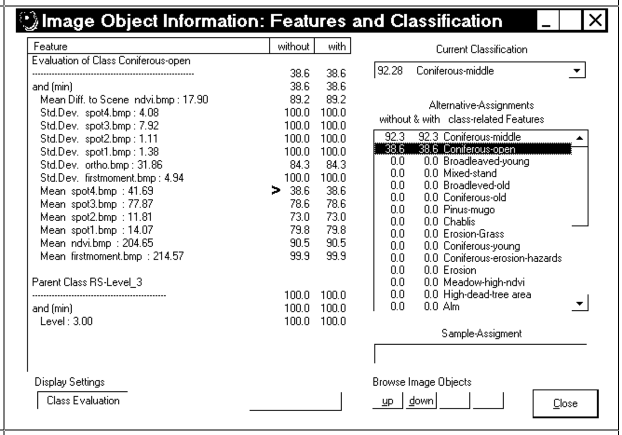

Figure 5. The 38.6% membership of coniferous-open depends upon the value in SPOT 4- band 4 (Infra red). The lowest value counts ('fuzzy AND as minimum).

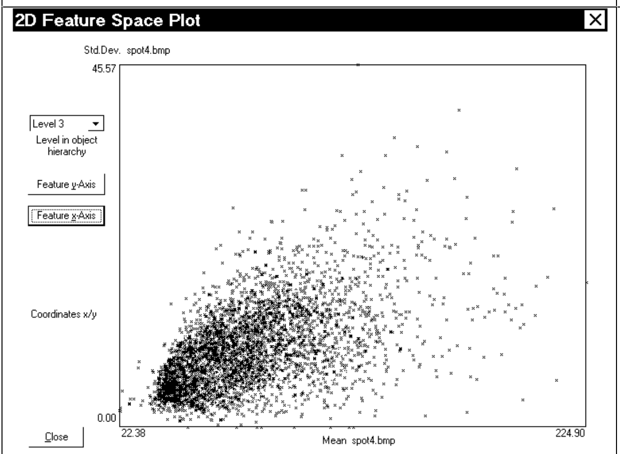

Figure 6. The SPOT-4 Band 4 infra-red, mean object values against Std.Dev. (Intensity vs. surface-roughness) There is no need to assume any correlation. Gaussian distribution can be assumed and in that case, the distribution should and is showing concentric circles of increasing density from periphery towards the center.

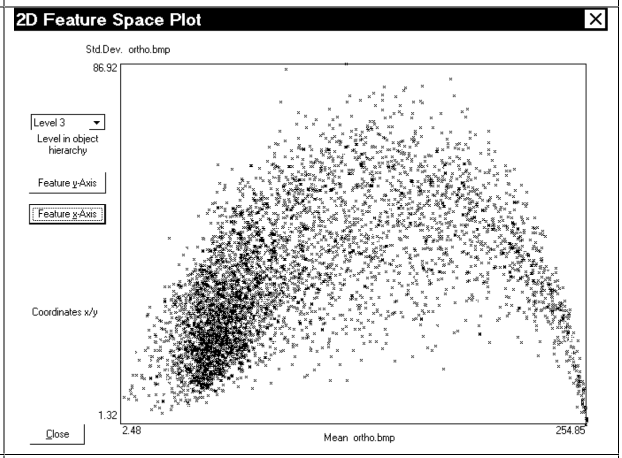

Figure 7. The same graphic as figure 6 using the panchromatic band. Gaussian distribution can not be assumed.

5 EVALUATION

The evaluation of the classification results is more complicated for object oriented analysis than a per-pixel classification evaluation, using a confusion matrix. Actually the traditional confusion matrix or K-factor (Richards 1999) for **class** evaluation is possible but too simple for object evaluation .A single large false-classified object has a huge impact on the K factor in comparison with many small correctly classified objects. Of course, evaluation according to visual check, as applied in traditional photogrammetry is always possible. Before overall accuracy assessment, individual objects are evaluated over their specific features. As larger overlap exist among sub-classes, here an example is given for a selected object in the sub-class *coniferous-middle*.. A specific object , not in the training set, of which terrain knowledge is available, is correctly classified as a *coniferous-middle* stand. The critical band here is mean value of band 4, SPOT –4 , infra red, giving a 92.3% class membership. The second class option, the object belongs 38.6 % to the class *coniferous-open* (figure 5) . Also in this case, mean value of Band 4 from SPOT-4 is the critical feature. Gaussian distribution can be assumed, explaining the shape of the fuzzy logic curves in figure 3. For other features, such as standard deviation of the panchromatic band, the Gaussian assumption is not quite correct. In this case a box classifier is better at place (see figure 2). Gaussian distribution can be checked in a 2-D plot of independent object features (Figure 6). An explanation for the shape of the graph in figure 7; Gaussian distribution for panchromatic data is corresponding to expectation for object mean value and standard deviation (range X=15-210).Mean value depends on photo count, standard deviation is a measurement of surface roughness. There is no factor that allows to assume that brighter objects are more smooth or vise versa. In very dark objects (shadow !), however variance is minimal. In very bright objects, the sensor saturates, therefore the variance turns to zero as well (Manakos, oral remarks). This curve is therefore a better indication for sensor sensitivity. The terrain knowledge allows a proper selection of typical representative objects and analysis of their critical features. After this phase, an overall evaluation can take place. For more automatic procedures, the difference between first and second membership function is an interesting one (Baatz,1999). In the case of the object in figure 4 and 5 this would mean 92,28-38.6=53.68. If this object would be 99% member of *coniferous--middle* and 97% member of *coniferous- open* the difference is only 2, Still the class membership is very high. This illustrates the difficulties of object evaluation and the deviation from class evaluation Until communis opinio on automatic procedures are not fully developed, visual check remains the basic evaluation procedure, but automatic alternatives are available and waiting for acceptance among the user community.

6 CONCLUDING REMARKS

The analysis on a per-pixel basis is not very useful in image data with high internal variance. To overcome this problem, an object based analysis allows a good solution. Object oriented analysis alone is not enough. In software like eCognition, a few bottlenecks are solved at the same time. First, a single database allows a full integration of GIS and remote sensing data. Using a hierarchical semantic network and a fuzzy logic 'query' facility on the database, the expert knowledge can be incorporated and the implicit information richness in the database can be fully exploited. Image and data fusion are a by-product from the visualization of the central database. The landscape model as defined in object layer construction and flexible database query through adjustable decision curves, requires much more terrain knowledge. This offers a extended role for the field expert. The software tools are very flexible and strong but the landscape model is very much depending upon user specifications. The landscape object model therefore is the crucial part of the analysis. For a specific application, exchange of modeling and object-sensor relationships becomes necessary between users. Spatial relationships in a hierarchical network is a rather new way of defining semantics between image and 'geo'- objects. Still this field is in full development and the results are promising enough to keep a keen eye on the developments. As literature showed, over the past decades there is a development in favor of object oriented analysis of environmental imagery and GIS data. Therefore these strategies are not a fashion flaw that comes and goes. This type of analysis is very well rooted in long term development and will dominate remote sensing research in the near future. Automatic accuracy assessment remains a very important topic. Confusion matrices are a too simple tool to achieve proper inside in the robustness of the classification. Only expert consensus can achieve the formulation of procedures that allow an acceptable level of automatic accuracy analysis. Object oriented analysis is here to stay; Educational remote sensing literature should add a chapter accordingly.

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