SEQUENTIAL PROCESSING OF IMAGE OBJECTS AND IT'S CONSEQUENCES FOR AUTOMATIC ANALYSIS

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ABSTRACT:

The spectral mean and standard deviation of a class in the spectral domain used to be a crucial feature to image analysis. The prime directive of image analysis was therefore focussed on establishing this mean and/or standard deviation of a class by the training phase using a proper selection of samples in the image domain. The large variety of attributes on image objects now makes it possible to start image analysis without defining a spectral mean and standard deviation of a class, but instead to concentrate on histogram extremes of a selection of classes. The predictability of certain classes in their extremes of their histograms allows for automatic establishment of a sample population. Such samples form the basis for spectral calibration of the rest of the sample population.

The initial understanding of the imagery started from object primitives that should have normal distributions in spectral feature space and therefore are spectral homogeneous. This was predicted in the pioneer work on ECHO of Kettig & Landgrebe (1976) where image objects were introduced. However, this still does not show the complete picture, as deviation occur due to spectral confusion as well as inhomogenities within the image. An important source of large spectral variable object-primitives in OBIA analysis are edge objects that do not behave as homogeneous spectral image objects and should be separated accordingly. The explicit registration and classification of edge objects offers new opportunities in object based classification.

Due to a sequential process approach in eCognition 5.0.4, a tailor made sequence of processes can be constructed for the classes within the legend. The sequences can be discussed with fellow experts and in this way reaching a maturity of a standardized process flow for standardized classes. Extending the knowledge on class behaviour is a necessity. Not only in the spectral domain of the feature space where is still a lot of spectral confusion. But moreover the increment of knowledge on behaviour in spatial relationships, which are often unique for a certain class. This makes full automatic image analysis possible.

1. SEQUENTIAL PROCESSING, A CAUSE FOR CHANGE

The latest development in object oriented classification is the construction of a workflow according to a sequence of processes. The original design of the hierarchical architecture of a class-tree now subordinates the design of a 'process-tree'. The sequential process flow changes the treatment of image objects in the scene most notably in operations that previous used to be image based operations. These image operations now have become part of object based operations such as segmenting only a single object-class or calculating a principle component for one class only and not for a set of spectral bands. This process approach facilitates a full automatic image classification. This causes major changes in the process flow of image object classifications which has consequences for the hierarchical classification schemes. Hierarchical classification is now taken to the extreme. Other important changes are automatic sampling processes as well as developments towards standardizations.

2. HIERARCHICAL CLASSIFICATION

Hierarchical classification is not a new phenomenon in remote sensing. The traditional output of such a classification is a stratification of the thematic layers. In the sequential process approach, such as applied in eCognition 5.0.4, the output goes beyond the stratification of thematic layers alone. The traditional stratification contains per layer one or a few element(s) of the legend. Moreover, the various classes are initiated using comparable procedures and the classes themselves were organized in a decision tree.

When switching from the traditional hierarchy of classes to the hierarchy of processes, there is a special process flow using a tailor made process designed for each of the classes. Although initializing the class itself remains important, the main focus stays with a correct transferability of the overall architecture of a process design. This is something very different than the architecture of a class tree design. The procedure should have a logical internal flow as well as reaching maturity on the processes of class initiations after discussion by fellow experts. This could imply that a compromise on class accuracy is acceptable in a trade off for an enormous gain in speed and quantity of imagery to be processed. Meanwhile expecting that when processes become mature they reach or surpass the accuracy of traditional hierarchical classification schemes.

2.1 Visualization

The simple decision tree visualization can not grasp the more complex flow of the process design. The process hierarchy deviates also considerably from the original class-tree hierarchical design which is part of the eCognition versions up till 4 and a new design for the visualization of the process workflow becomes a necessity. A preliminary design is used in chapter 4.1 Figure 3 for a simple start-up case. The visualization is however in its very infancy and although the process is functional, the simple decision tree for hierarchical classes can not be easily adapted for the visualization of the sequential process flow. For the visualization of the sequential processes, UML based design (after Booch et.al., 1998) is more likely to be effective and as yet still under development. In practise this would force the operator to be very familiar with the typical discriminating features of the objects of interest to keep track of the overall design and process flow.

2.2 Predicting class behaviour

Because the hierarchical architectural concept of the original class-tree design is now transferred to the hierarchy of the process based classification, the step by step approach of each of the processes allows an in depth manipulation of image objects using a large variety of operations. This large variety of process operations now also allows for 'a farewell' to the strength of pure statistical methods like cluster analysis or minimum distance to mean algorithms. In statistically dominated analysis, the initiation of the thematic layer is achieved using a mean and standard deviation of the samples. Traditionally, the operator had to select the correct pixels or objects in the image domain. In the new approach, the operator must now explicitly formulate expert knowledge into the expert process without the need for sampling in the image domain. The knowledge on the object class (predictable) behaviour in feature space has to be considerable. The operator has to differentiate classes with an easy statistical description (water) from classes which are easy to discriminate using spatial attributes (buildings). The final user might continue 'Click & Classify', but to initiate the class of interest, the 'click' operation should not be focussed on a class inside the image domain returning coordinates, but instead, the user should just click inside the legend.

2.2.1 Representative by definition: The peer experts will be the referee on the discussion over the conditions which are considered to be crucial for representative populations. Because much of these standard features are encountered from empirical data and few can be predicted from theory on image understanding alone. The latter procedure is of course preferable as empirical definitions are merely a rule of thumb and should be backed up by sound theoretical knowledge on the cause of predictable behaviour of image objects. A typical example is the low standard deviation of the red band over forest areas. The shadow component as well as crown activity both reduces red band albedo values over forest. However, aging forest stands seems to be reducing this albedo more than young forests. A theoretical explanation on the bio-physical properties of aging forest stands and the theoretical reason for the relationship between forest age and low standard deviation values in the red band are of much more value than the simple statement, 'use low standard deviations in red' to classify a forest mask.

2.3 From Area to Point analysis

Furthermore, the GIS output of image objects in the hierarchical process design maintain their attributes. This has an enormous impact on further GIS modelling. This can be demonstrated easily in the conversion of a standard output of an area feature. If a problem in an analysis of an area feature can not be solved or more easily be solved in a GIS-line analysis or even a point analysis, the lines and points will be derived from the area feature of the OBIA-output. The neighbourhood of image objects, their arcs as well as the triangulation of the object centroids are three crucial levels for spatial analysis. Merging these levels will become indispensable in change detection concepts.

2.3.1 Polygon defining arcs are more than area definitions: An image object incorporate features valid within it's borderlines as well as on each of its arcs touching the neighbouring object-arc. In standard GIS, the set of arcs per area feature describe the enclosement of the area but normally not register the deviations of each arc towards the neighbouring arc. This information is explicitly embedded in an image object knowing it's neighbourhood. It remains curious that this bordering-arc information is assigned to the area feature image object and not to the arcs themselves. The Arc however can be simulated by registering the border edge as an independent object. This is for the time being an acceptable work around and used in chapter 4.2. The neighbourhood information can also be assigned in a limited amount towards it centroid. In this way reducing part of the area and line information to the point. The point feature can be treated in normal GIS software. Extending the overall facilities of OBIA software however would be able to integrate this option as well.

2.3.2 Change detection: The conversion from area to point feature is crucial in change detection analysis. Here an analysis of a point triangulation using centroids per object can thus replace a neighbourhood analysis using polygon border features (after de Kok et.al, 2005). Many changes in image objects do not have a major effect on the centroid of the objects as well as the spatial context of centroids among their neighbours. Spectral changes due to sun angle, acquisition date as well as vegetation development stages do not change centroid positions. Also small border changes that cause so called 'slivers' account for much of the 'changed pixels' but have little effect on object centroids. Real changes should be realized by disturbing the centroid triangular network in their sequence, disappearance or new appearance as well as in their centroid neighbourhood. Reducing change analysis thus from an area problem to a point change problem and back to changed image objects (area feature) would resolve much of the noise encountered in standard raster based change analysis procedures.

3. SAMPLING

3.1 Template matching

The strategy of predefining features in sequential processing is not uncommon and resembles in its assumptions the traditional template matching technique. In template matching, no sampling is required. The traditional template functions within the image domain. The process-template however functions not inside the image domain but in the feature space domain. The decision on the population that is regarded representative for a class thus no longer liess solely with the visual interpreter of the image. The selection of a sample population comes forth out of a number of rule that describe the behaviour of the sample set which is to be regarded representative. Therefore the sample selection is not left to the chance of the operator to encounter a set of sample in the image which 'seems' to be a good start but to follow explicit rules about the *must have* conditions for samples to be ensigned candidates for the representative population. As in traditional template matching, there is a strict expectation towards the object population within its domain. The success lies in the correct treatment of histogram extremes for the crucial classes. This is possible because certain crucial classes behave predictable within the histogram extremes of a selected group of features. The template with a fixed description in pixel/vector size and shape can now be replaced with a standardized set of process-rules for an initial categorization.

3.1.1 Categorization: Categorization can now precede class construction. The categorization is using feature based category descriptions preceding final class-names from the legend. As an example a category name; *high textured, high NDVI value objects containing shadow-sub objects* is used instead of the legend class name '*broadleaved forest'*. The categories behave differently towards accuracy assessment compared to the legend classes. The final classes in the legend must compromise in accuracy due to generalization issues, where mere categories simply follow process decision rules and should always be accurate.

3.1.2 Accuracy: Creating a correct set of categories is a process which can mature due to expert consensus. Final classes in the legend involve user requirements on generalization issues and priority issues over the trade off between failures of commission and/or omission. Overall accuracy of 80% might seems rather low but if there is a certainty that the 20% failure are only omission failures, the user defined application can be better served than a 95% overall accuracy where 3% commission failures triggers too many false alarms. Even finding 98% correctness on the categories of '*sharp contrasting edges'* and linking them to buildings does not give guarantees over correctly classifying the class *'dense urban fabric'*. However the correct assignment over which contrasting edges belonging only to buildings is a very essential standard process in the process of becoming mature and overall applicable for VHR data.

3.1.3 Self-adapting: The processes are self adapting towards the changes of the spectral values in each varying image scene of the same mosaic due to the ability to let the process measure a spectral and/or spatial value on a selected object class population and assign the measurement to a process variable. Thus traditional template matching works in the image domain in cases where the image domain is predictable hence the new process approach works in feature space because the histogram is predictable. By making the list between crucial classes and their predictable feature behaviour complete, robotic vision comes within reach.

3.2 Sampling as solitary job

Classical sampling is a solitary operator job, which main purpose is to select the representative population for each class, using this population to define a mean (nonparametric classifiers) and/or a standard deviation (parametric classifiers) for a particular class. New ways of sampling allow pre-defining a standard rule for a crucial category based upon stable and transferable spatial relationships and valid for a range of sensor types.

For example *'maximum contrasting edges with high standard deviation of the red band'*. This example is a textural/procedural description of a template. This template is crucial.

The crucial category or crucial class of contrasting edges exist where infrastructure and build up areas appear in any image of VHR type (4 meter resolution and higher) and can be easily verified by any user that deals with image object analysis. The edge information inside an image requires an extensive excursion into human perception and human nature and can only be lightly covered within this article. Fundamental research into the feature detection and categorization of edges promises to open up a new chapter in remote sensing.

3.2.1 Edges as a must have condition: Basically people separate nature from their dominion by explicitly constructing a physical edge and a connecting infrastructure (wall, fence, city and road) or by their treatment of nature (agricultural parcel, forest-stands) with of course exceptions like the Scythian burial mount, which cast almost no shadows. Despite the very rare exceptions, physical edge construction is here assumed to be a standard phenomena in populated environments and crucial to any class description containing anthropomorphic features and the basis for topographic maps. The pixels registered on the edges of real world objects are responsible for much of the spectral confusion within an image. The pure spectral mean of an edge has therefore little meaning. Separating the edges from other more homogeneous surfaces and use spectral image analysis for non-edge objects alone is preferable. While the object-population of contrasting edges is a must-have condition for anthropogenic objects, they contain unique as well as non-unique features. Their behaviour towards the standard deviation in the red band is unique. Their NDVI values are not unique. They share similar NDVI mean values (not NDVI standard deviation values!) to all other non-vegetative areas. Although it has been stated that the pure spectral mean of an edge object has little importance as there is no predictable mean value in feature space of the class 'edges' in the NIR or Red band, the Ratio value such as the NDVI, still contains meaningful spectral information.

3.2.2 Anchor Objects: The contrasting edges can be defined as anchor objects. Anchor objects should be automatically detectable and the measurements on these anchor object should be representative for a much larger class of image objects. The extreme contrasting edges with high standard deviation of the red band will always belong to non-vegetative areas, if available in the scene. After automatically measuring their NDVI mean value in each scene, they can be used as automatically detected samples and now used for mapping all other objects without vegetation. The contrasting edges are just one example of a set of crucial objects each with their transferable attributes. A list of crucial objects per class would suffice to indicate its class potential to be mapped full automatically. The main aim becomes now to define standard rules which are used for crucial classes to establish a population of anchor objects within the scene. The initiation of these anchor objects allows measuring spectral characteristics of this particular scene and assigning these measured values to a process variable. Then using the values from the process variables to detect the thresholds where a critical class separates itself from all other classes. If such as unique separation can be found, the mean and standard deviation of the class is not a decisive factor, because overlap in feature space can be expected to be very small under such conditions. These conditions will be clearified in 2 cases using various optical sensors as well as a Lidar edge analysis.

4. CASE STUDIES

4.1 VHR Analysis

The first Case shows a universal set-up for VHR Imagery such as IKONOS and Quick bird scenes. A pre-processing step is essential, where a 'texture image' splits all objects in high and low textured areas. Texture image derivatives are known for their large variability as well as their redundancy. From experiences with Haralick textural features (Schleicher et.al. AGIT 2003) our research has moved towards a texture map based upon edge detection filters. Due to the redundancy, this texture derivative is very similar to the Haralick homogeneity feature (known as IDM in Steinnocher, AGIT 1997, compare also fig.1 and fig.2). Since this much cited Steinnocher article and the accompanied software, texture analysis on panchromatic images has evolved in our research from texture calculations in a fixed window size towards texture analysis per object in eCognition version 4 and later (Schleicher et.al., AGIT 2003). Continuing with the pre-advantage of the texture analysis applications in image analysis over the years, a new variance on IDM has been developed using the central cause of an important element of the texture map namely the mixed pixels that share various spectral distributions of its neighbouring surfaces and can be found exactly at the edge of two different distributions, preferably only 1 pixel thick. The pre-advantage of this texture map is the ability to calculate the object feature "contrasting edge". This texture map is produced by dividing an intensity image by the edge image(s) Here the Pan band was used, the edge image is a sum of *Border* and *Frame* (Wezyk & de Kok, AGIT 2005), which are edges created by the difference of the original pan-band minus the *Lee-Sigma* filter result.

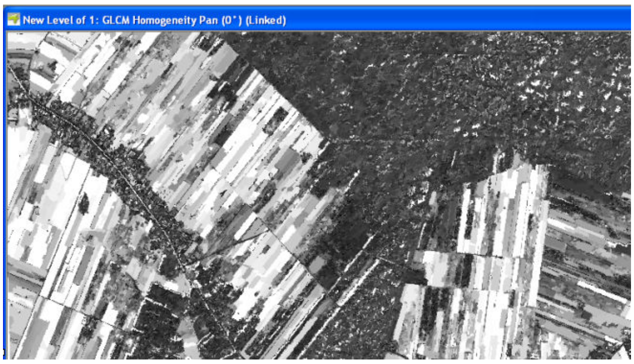


Figure 1, Homogeneity or IDM textural image (derived from a Quick bird scene in Wezyk & de Kok , AGIT 2005)

Figure 2, Similar to fig. 1, a textural image based upon intensity divided by edges (detail description of process-creation in Wezyk & de Kok AGIT 2005)

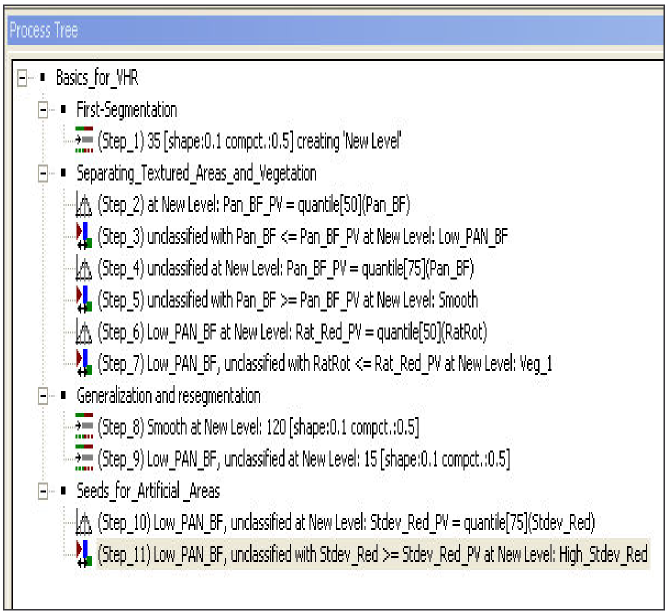


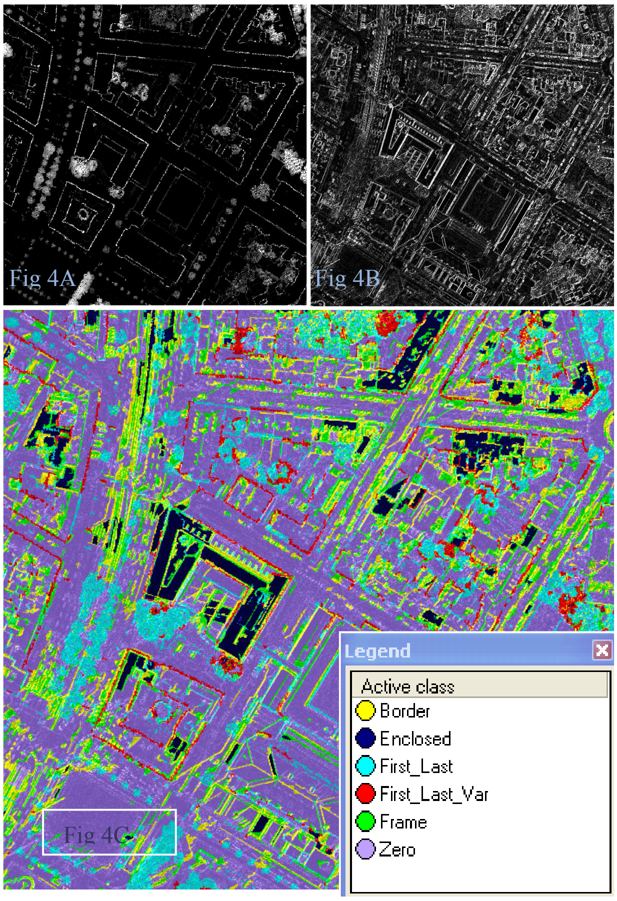
Figure 3, The process in eleven steps for initial VHR analysis

4.1.1 Eleven standard steps

Eleven standard steps: Like any OO process we start with initial segmentation with scale_factor 35, using Pan with weight 5 and Border Frame weight 3. (see figure 3, **step 1**). In **step 2**, we measure the lowest 50 Quantile of the texture Histogramm. In **step 3** this 50 Quantile is classified as Low-Pan_BF. These objects have a low value for the textured image which means low grey values for Panchromatic band divided by the sum of Border and Frame (Wezyk & de Kok, AGIT 2005). This Category with alias name Low-PAN_BF always contains artificial areas and forests in any European and North Amerika VHR satellite imagery. The opposite category, Smooth with the more than 75 Quantile values of Pan-BF (**step 4** and **5**) always contains mainly agricultural areas and water. In **step 6**, the highly textured category including forest is measured for their lower value of the Ratio of Red and thus classified (**Step 7**). Here Red is divided by Blue+Green+Red+NIR+PAN. This makes a better Ratio than the NDVI, as we can incorporate the effects of the high resolution of the Panchromatic Band. Where normally the NDVI is bright, the Ratio of Red has low values and vice versa. Remark that in Step 7 the vegetation part is taken out into VEG_1, therefore Low-Pan_BF contains after step 7 mainly artificial areas. The agricultural areas within the category Smooth are generalized in **step 8** to reduce the total amount of objects. In **step 9**; after general object amount reduction we are able to increase again the total amount of a more interesting object group by applying a re-segmentation with a lower scale factor of 15 only for both the categories artificial areas and the remaining unclassified regions. Remark that the larger objects of the Category Smooth are left untouched. This step 9 has become possible in the new process approach and was not part of previous eCognition versions where always an image layer was segmented. The smaller objects in the category artificial areas allow to measure (in **step 10**) the highest values for the small edges around build up areas which are above the 75 Quantile for the standard deviation of the red band normalized for size (here StDev_Red/(Area^(0,5)) and than classified (**step 11**). With these 11 Steps we have now automatically derived Training Areas for the categories Build up Areas, Forests as well as Agricultural areas.

4.2 Lidar Edges

The LIDAR analysis starts with a focus on Edges detectable by the difference of first and last pulse as well as the edges derived from the optical data (aerial-image, NIR band) through the *Lee-Sigma* difference operation (Border and Frame see Wezyk & de Kok, AGIT 2005). The LIDAR pulses on a building edge create a large difference between first and last pulse. A Geo-Tiff derived from the point cloud of differences between First –Last LIDAR Echo shows an incomplete part of all Edges of real world objects, mainly buildings and trees (Fig.4A). The difference image does not deliver complete closed edge information so constructing complete building outlines as a shape file is not a simple task. The missing part can be made more complete by adding edge information from the optical data. The case study shows the intitial start of an urban analysis.



Figures 4A, 4B and 4C, original image, courtesy of www.toposys.com.

Fig. 4A; A GeoTiff derived from the point cloud of differences between the first and last echo of the Lidar pulse. The building edges are very well visualized.

Figure 4B; This shows edge information from the optical data. Remark that sharp edges of roofs from optical information are an important source for the description of the reflecting surface roofs and the further basis for aspect definition of roof surfaces.

Figure 4 C, This shows the result after 11 process-steps where an initial category '*Enclosed*' delivers the sample class to measure roof features from the image for further classification.

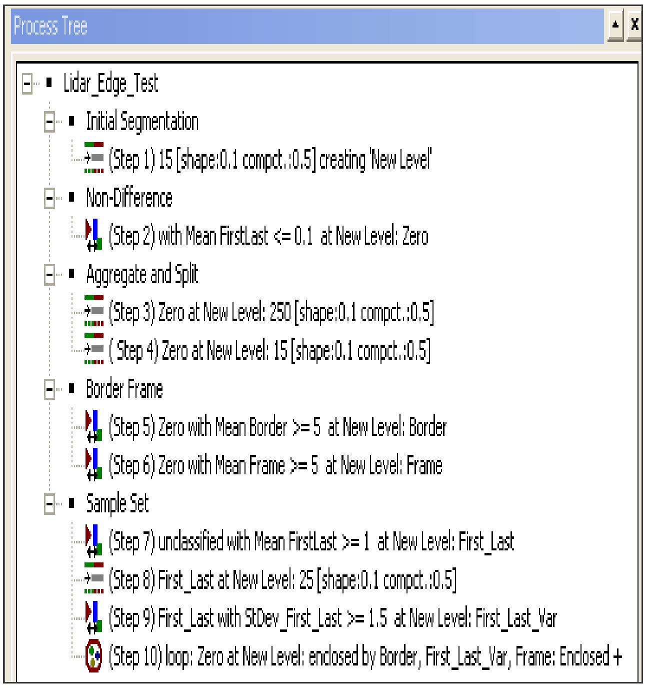


Figure 5, the 10 initial process steps on LIDAR edges.

4.2.1 Lidar edges in 10 Steps

In **step 1** (Figure 5), segmentation takes place on the GeoTiff containing First-Last LIDAR pulse alone (Scale 15, weight 1). This creates objects (in **step 2**) with and without a large LIDAR difference and thus separates the population of edges and tree-crowns versus all the rest category of '*Zero*'.
In **step 3** all non-LIDAR edge objects (*category 'Zero'*) are first aggregated with a large 250 scale factor for NIR, RED and Green. In **step 4** finer segmentation takes over using only Border and Frame optical edge information. In **step 5** and **6** these optical edges are classified. In **step 7**, the LIDAR edges are assigned the category, First-Last. In s**tep 8** this LIDAR edge category is aggregated. The LIDAR edges after aggregation have a high standard deviation of First-Last difference for edges belonging to buildings than compared to the general lower standard deviation of edges of tree-crowns and can be separated in **step 9** using the category First_Last_Var. In **step 10**, all objects which are enclosed by optical edges, Border, Frame as well as those enclosed by high standard deviation of LIDAR edges are assigned 'Enclosed'. This category 'Enclosed' is an automatic sample population to measure the features of roofs of the building.

5. STANDARIZATION AND OUTLOOK

Sampling by a single operator for the purpose of establishing a mean and a standard deviation for a class is a subjective task. Discussing the sample selection with fellow experts is useful for a single scene but not transferable for all other scenes. The sequential process workflow however allows discussing each step within the process with fellow experts. A good example is Case 1. Here each of the 11 Steps can be meticulously debated by fellow experts and transformed in a standard set for splitting any IKONOS or Quick bird image into a texture class as a standard protocol for extracting automatic samples for any Land cover classification. This discussion would lead to objective process-protocols. If the evaluation is positive, the line (set) will reach maturity and allows for standardization of the process (lines). They will become applicable for standard classes for each sensor type. This opens the way to full robotic land cover classification or full robotic counting as part of automatic feature detection such as counting ships, cars, trees etc, which in this intial stage already can be demonstrated (de Kok & Wezyk, 2006)

5.1 Edge imagery

The information content of pure edge images which are used to create figures 4A, B and C suggest that such visualizations deliver two indications at the same time; Edge visualization reduces the normal complexity of 8 and 11 Bit data in several multispectral as well as panchromatic bands in an almost zero-one imagery, (edge, non_edge). At the meantime preserving essential details in the image information implicitly existing in the original imagery. An easy control-test is established by a visual digitalization on screen of a pansharpened image while comparing the results with a digitalization of the edge image alone. The user will be surprised to realize the similarity between the extracted results. Because the human eye and the way the visual interpretation can work so easily with edge imagery alone, it would offer itself to computer analysis to reduce image interpretation first to a correct classification of an edge image and mimic exactly the human interpreter. Ongoing research on pure edge classification in our forest analysis reveals how useful this information is in the initial stage before the consequential full image classification process using the spectral values. Above all, the relative insensitivity of edge information on differences of acquisition date and sun angle as well as atmospheric conditions (except clouds) not to mention their stability and transferability over scale and sensor type make them unique image objects. Although edge imagery is a classical results of standard remote sensing software, the classification of edges seems to be still an undiscovered territory.

5.2 The quest for image understanding

The step by step approach of the processes allows task sharing between expert groups. One being responsible for the automatic cloud detector, another for the forest-type mask or settlement masks. Standard libraries for automatic image analysis have the potential to evolve in similar structures like libraries for numerical recipes. Hence reviving the old dream of signal separability of classes that was underlying the ECHO concept (‘The **E**xtraction and **C**lassification of **H**omogeneous **O**bjects’) by Landgrebe 30 years ago. This would imply a continuous effort for a ‘*broader, more fundamentally based research on understanding the signal response’ of material in laboratory as well as in the field environments* (after Landgrebe, 1997). Following Landgrebes advice we continue expanding the signal response research. A long and tedious ongoing work with presentable intermediary successes.

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