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Conference paper STRC 2011

STRC | 11th Swiss Transport Research Conference
Monte Verità, Ascona, May 11 - 13, 2011

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28 January 2011

Abstract

This research study addresses issues of transport modeling aiming to the recognition of vehicles, with perspective to generate a knowledge base for an automatic recognition of vehicles from similar type of data. Based on two datasets consisted of multi-spectral data of an RGB/NIR line scanner, intensity data and elevation data of a LiDAR scanner, the goal was achieved with an object-oriented and fuzzy logic approach. Nevertheless, an object-oriented image analysis comprises of multiple complex dependencies that is required to be reduced for the achievement of an optimum accuracy in classification. Namely, via a series of tests was attempted to build simplified hierarchies and class descriptions that additionally would act in compliance with the criterion of homogeneity. Regarding this criterion and due to the shape and diminutive size of the object in question, a classification would be rendered inaccurate without the utilization of the most possible colour criterion and the most necessary shape criterion.

The process of object-oriented analysis included three levels of segmentation that were later classified based on descriptions drawn up for the photointerpretation classes, which were recognized in the two datasets that were provided. Initially, the data were processed and analyzed with two approaches based on object-oriented analysis, and the resulted classes were described with fuzzy logic. From the "top-down" approach large surfaces of various land uses and several types of vehicles were ensued, avoiding misclassification of lorries. From the second, "bottom-up" approach, various types of vehicles emerged as compact objects, after merging the resulted objects that were precisely describing parts of the actual objects of classes. With focal point the vehicles extraction, the description of the vehicle class was assigned without significant overlap in the range of features used to describe other classes, rendering to a greater segment classification accuracy of the objects that were depicting vehicles. Despite efforts to produce suitable segments during the segmentation of this level, due to the size of the vehicles in the given data resolution and of the errors resulting from the general classification, vehicle shape could not be properly defined in extent.

The developed methodology can be serve as a guide for recognizing vehicles both in urban and industrial environment from the same resolution of multi-spectral and LiDAR elevation data, by effectuating minor alterations in the range of features that has been employed.

Keywords

vehicle recognition – vehicle detection – object-oriented analysis – object-based classification – fuzzy logic – LiDAR-based segmentation – multi-spectral data – object extraction

1. Introduction

The image analysis and processing with pixel-based techniques that were widely used in previous projects are no longer considered as reliable, as they are human-induced. In the current study a relatively new type of supervised classification was used, the object-oriented analysis; this is based on polygons-objects that are resulted from sequential segmentations. The study object was the vehicle in both complex urban and industrial environments. Multi-spectral, intensity and altitude datasets rendered the vehicle recognition possible.

Object-oriented analysis is based in the principle that the meaningful information for the image interpretation is not efficiently represented by individual pixels, but by objects with spectral and geometrical features and by their interdependencies. In order to mitigate the complexity of those dependencies, the simplest structure of hierarchies and class or features' description was implemented, along with the minimum number of segmentation levels, segments, classes and features that would lead to a better classification of the objects in question.

The coarse analysis level was formed via the top-down approach, with main objective to identify most of building surfaces and minor to extract vegetation surfaces, soil surfaces or the road network. Due to potential confusion with other classes, certain building surfaces was decided to be classified in a finer level. As in every segmentation level, the coarser possible segmentation was applied, by setting the maximum value of scale parameter, so as to derive the finest and most correct photo-interpreted objects, which would comprise one and only type of land use. A classification-based segmentation was then implemented, aiming to a better definition and classification of the objects in the general class of buildings. The new merged objects of similar land uses were again classified with only slight alterations to the class descriptions, utilising as such the maximum information of this level of analysis. The completion of identification of all building surfaces was introduced after the end of the segmentation and classification of the medium analysis level (level 2). The purpose of creating the current level was the marginally better distinguish of buildings' surfaces and of low flat roof buildings, so as to avoid misclassification of lorries in this category.

The fine segmentation level resulted from the top-down approach with main aim the classification of vehicles. The buildings' surfaces were projected from the coarse and medium analysis level, therefore no further attempt of determine them was made, which significantly reduced the size of the study field for vehicles. Due to the limited size of objects, the identification of surfaces with low/bushy and high/arborescent vegetation, sparse vegetation and soil, road network, dark and light asphalt surfaces were rendered possible. However, the focus was set on vehicles' recognition and parts of them, reason for which the classification accuracy of objects that were depicting vehicles was greater than that of other classes. Despite the attempts to segment suitably the level so as to alleviate the recognition of the objects in question, due to their size in the given analysis level and to the errors resulting from the overall classification, their shape requires further study so as to be determined precisely.

The object-oriented tool that was used prohibited the addition of layers during the segmentation and classification processing. Driven by that and by the ambiguity of photo-interpretational segregation in surfaces with soil and vegetation with buildings' shadows, potential layers that could contribute to better classifying the land uses were created. Aiming to accentuate their differences, a pixel-based analysis software was used to pre-process the data. Namely, the layers that emerged were a normalised surface elevation model (nDSM), product of the subtraction of the digital surface model of high values of last pulse and of the digital terrain model (DSM LEH – DTM) so as to obtain an elevation model with the actual altitude of the objects, and layers with filters that were imposed to emphasize the regions with high spatial frequency that correspond to edges – edge detection filters – and to mitigate the heterogeneity inside the structures of the same land uses.

1.1 Data Description

The data that were used in the current study are of the TopoSys co. that performed measurements with a combination of laser scanner (LiDAR) and linear RGB/NIR CCD scanner, which resulted to the following elevation, spectral and intensity data.

1. Digital elevation models
   A. Digital Surface Model (DSM)
      A.1. Digital Surface Model First Echo (DSM FE)
      - Digital Surface Model First Echo Highest values (DSM FEH)
      - Digital Surface Model First Echo Lowest values (DSM FEL)

      A.2. Digital Surface Model Last Echo (DSM LE)
      - Digital Surface Model Last Echo Highest values (DSM LEH)
      - Digital Surface Model Last Echo Lowest values (DSM LEL)

   B. Digital Terrain Model (DTM)
   C. Digital subtraction models
      - DSM FE – DSM LE
      - Normalised Digital terrain model nDSM (DSM FE – DTM LE)
2. Intensity data
3. Spectral data in four spectral channels Red (R), Green (G), Blue (B), Infrared (IR)

1.2 Study area

The datasets that were used in this study were two sections size 516x390 pixels (dataset 1, urban zone) and 1000x1000 pixels (dataset 2, industrial zone) that contain a large variety of categories and subcategories of land uses. Following is presented the entity of the classes that were recognized for the industrial zone image, hereinafter called as dataset 2, in a natural colour composite RGB:3-2-1 and in the false colour composite RGB:IRRG 4-3-2.The land uses are juxtaposed with the fine and medium analysis level, where they have already been classified and can be recognized by colour.

2. Methodology

2.1 Image Analysis and Pre-Processing

In the datasets that will be analysed with an object-oriented method, it was not rendered directly possible the photo-interpretational segregation between roads and impervious materials under shadow or not due to higher objects such as vegetation and buildings, increasing by that the risk of not classifying objects that represent vehicles in the corresponding class. For the enhancement of these categories reflectance diagrams were studied that were emerged by the mean values of each category for the channels Red, Green, Blue, Infrared.

In the reflectance diagram of vegetation the maximum values of reflectance are observed in the infrared channel and the minimum in the blue as expected, given that the blue channel does not penetrate in vegetation surfaces, as the majority of incident radiation is absorbed, whereas the infrared channel has been designed to reflect the radiation of the vegetation surfaces and represent them with white to light grey tones compared to neighbour thematic entities. By subtracting the blue channel from the infrared, that is their pixels, the image that emerges contains vegetation surfaces with high digital values, so greater brightness than the other surfaces, and thus that are easily distinguished.

Likewise, in the reflectance diagrams of buildings and roads, it is observed that the maximum reflectance values are appeared in red channel and the minimum in blue. This is justified by the fact that the red channel is designed to distinguish man-made structures. By subtracting the pixels of blue channel from the ones of the red, the resulted roads and buildings are represented brighter than the rest of the thematic entities and thus more visible.

The derivative of the subtraction between the DTM and the DSM is a normalised digital surface composite (nDSM) with objects above the ground with approximately their actual altitudes, since DSM represents the earth’s surface including objects on this, while in DTM all the objects have been deleted. For the mitigation of the diversity inside the structures due to noise and to sub-objects, which is not corresponding to reality as the digital values of an object must be even or at least to vary within a small range, the application of a median filter of size 5x5, in order to respect to the size of the objects and avoid information loss and generalization, ensured the best balance between achieving high homogeneity inside the structures and low loss of information at the objects' boundaries.

For the enhancement of the objects' boundaries, in particular of the smaller ones' such as the boundaries of vehicles, the slope edges' enhancement filter is applied that result in edges with altitude information.

2.2 Object-oriented Analysis

The object-oriented analysis contains various complex dependencies (Hoffmann, 2000). To reduce the complexity in this study, a series of tests was undertaken so as to distinguish the simplest possible construction of hierarchies and features' or classes' descriptions, the minimum number of segmentation levels and of segments, of classes and of features that would contribute to correctly classify the objects in question. It has to be highlighted the fact that the various bits depth layers that were processed comprise variations in the amount of contained information. The thematic layers with higher bit depth have greater effect on the outcome of the segmentation, since a single scale parameter is implemented to all levels. Different weights were applied to the layers in order to produce the same amount of information by layers with greater bit depth. At lower bit depth layers, higher values of weights are imposed, since it is more probable two adjacent pixels to have identical spectral value in the 8bit database than in the 32bit.

During the layers' formation of dataset 1, dark surfaces were emerged in various spatial locations, originally considered as noise. However, during the process of editing classes and describing their features for the classification of the land uses of this dataset, empty pixels were revealed in the DTM and in the blue composite, possibly due to failure of the optical device of the laser scanner system to record during the measurements. Thus, the classification and further analysis of the dataset 1 was rendered impossible and the automatic vehicles' recognition was restricted to the second dataset.

In the dataset 2, the two principal approaches of object-oriented analysis were used for the classification of land uses and the identification of the various objects in question. In the *top-down approach*, with initial the coarser-general classification, the aim is to classify the segments-objects as general classes of man-made structures and vegetation. Based on that level the smaller objects of the finer level are extracted, so it has to be defined with great precision. The objects that were classified with the current approach were man-made structures, such as various types of roofs, and with less precision road and rail networks, vegetation surfaces, such as arborescent, bushy, grass-covered and low-sparse, soil and cement surfaces and few parts of various vehicles' types.

In the *bottom-up* approach, starting from a fine scale analysis, very small segments that describe the data are formed, which the merge of them create objects of the class under examination. The vehicles' class was resulted from that approach, as entire objects or as clusters of them, and certain parking lots.

For every classification level the objective was to create classes that would be fully defined and classified with precision, so that to project them to other analysis levels without transferring the errors as well.

2.2.1 Segmentation Process

The general rule is to apply the coarser possible segmentation, by the use of the maximum value of scale parameter, so as to produce the largest but finest and most right photo-interpreted objects, which contain only one land use. In addition, for a successful process a homogeneity criterion is employed, which is an application of as much of colour criterion as possible and as much as shape criterion as necessary, for producing image objects of the least border smoothness and compactness (Definiens-Imaging, 2002). Otherwise, the segmentation that would result with the minimization of the colour criterion would comprise rough boundaries' objects, and with the minimization of the shape criterion the consequent layer would be consisted of objects with various land uses in the same segment. In these extreme cases, either the spectral or the geometrical information is not attained.

2.2.2 Classification Process

The segments/objects that occurred from the segmentation were classified through the formation of hierarchies for classes, classes' description and features. The goal that was set for every classification process was to classify as plenty as possible segments to the correct classes, so as to use the embedded information for structuring as well the classes of other levels. Each class description was emerged with fuzzy classifiers through membership functions and nearest neighbour method that permit a more precise property definition and consequently a more successful classification.

Membership functions are used as a method of converting a range of attribute values from arbitrary to continuous [0, 1] so as to comply with the rules of fuzzy logic, after evaluating each feature with mathematical operators. Therefore, there is a possibility of evaluating the attributes of all dimensions and ranges in a common base. The slope of the graph of each membership function describes the calculation of the assignment value for that function for a specific object feature. The main types of functions that were used in the current study are of form S, Z, trapezoid and the singleton function. In each function the assignment value of each object for the feature described, is represented in the Y axis with a value in the [0, 1] range, whereas the range of values of each feature that is used to describe a class in which any segment-object in question must belong to so as to be classified under it, is represented in the X axis. If a class is described by a feature that serves as a classification criterion and the value of an object belongs to the range of values of the feature, then the assignment value of the object to the feature can be determined using the distribution of the function. As the classes are defined by several features, the assignment value of each class is calculated by the combined values of the objects and the operations that the logical operators – and (min), and (*), or (max), mean (arithmetic), mean (geometric), not – that associate them determine. An example of a class description is the following:

IF	mean nDSM > 3
AND	scaled NDVI < 102
OR	area excluding inner polygons > 900
OR	mean difference to scene of DSM LEL > 1.98
THEN	classify segment as object of the “Buildings General Coarse Level"

The feature scaled NDVI is a variable that was created based in vegetation observations and that served as an innovative feature for recognizing the objects in question. It is calculated as the ratio of the difference of reflectance values between the NIR channel and the R channel to their sum:

$$ScaledNDVI = 100 \cdot \left(\frac{NIR - R}{NIR + R} + 1 \right)$$

The variable depends on the amount of chlorophyll and humidity in vegetation and soil. The red channel has been designed to record in the absorbance area of chlorophyll and the infrared to display high reflectance in vegetation surfaces, which are depicted with very light tones versus to neighbouring thematic entities such as water and soil surfaces, thus the identification of vegetation is evident. The range of values of the scaled NDVI [0, 200], in comparison to the normalized NDVI with range [-1, 1], is adequate to be represented in an 8bit image and ease the application of thresholds. Thus, the creation of more distinct classes mitigates the limits overlapping in the classes’ description.

In the cases that the description of certain classes demanded the involvement of several features, the nearest neighbour method was employed. The objects are classified based on their spectral values in a given feature space and with the contribution of training areas. In the current study, this method was considered as a fuzzy classifier with assignment values computed by the distance between the sample and the object in question as follows:

$$d = \sqrt{\sum_f \left(\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right)^2}$$

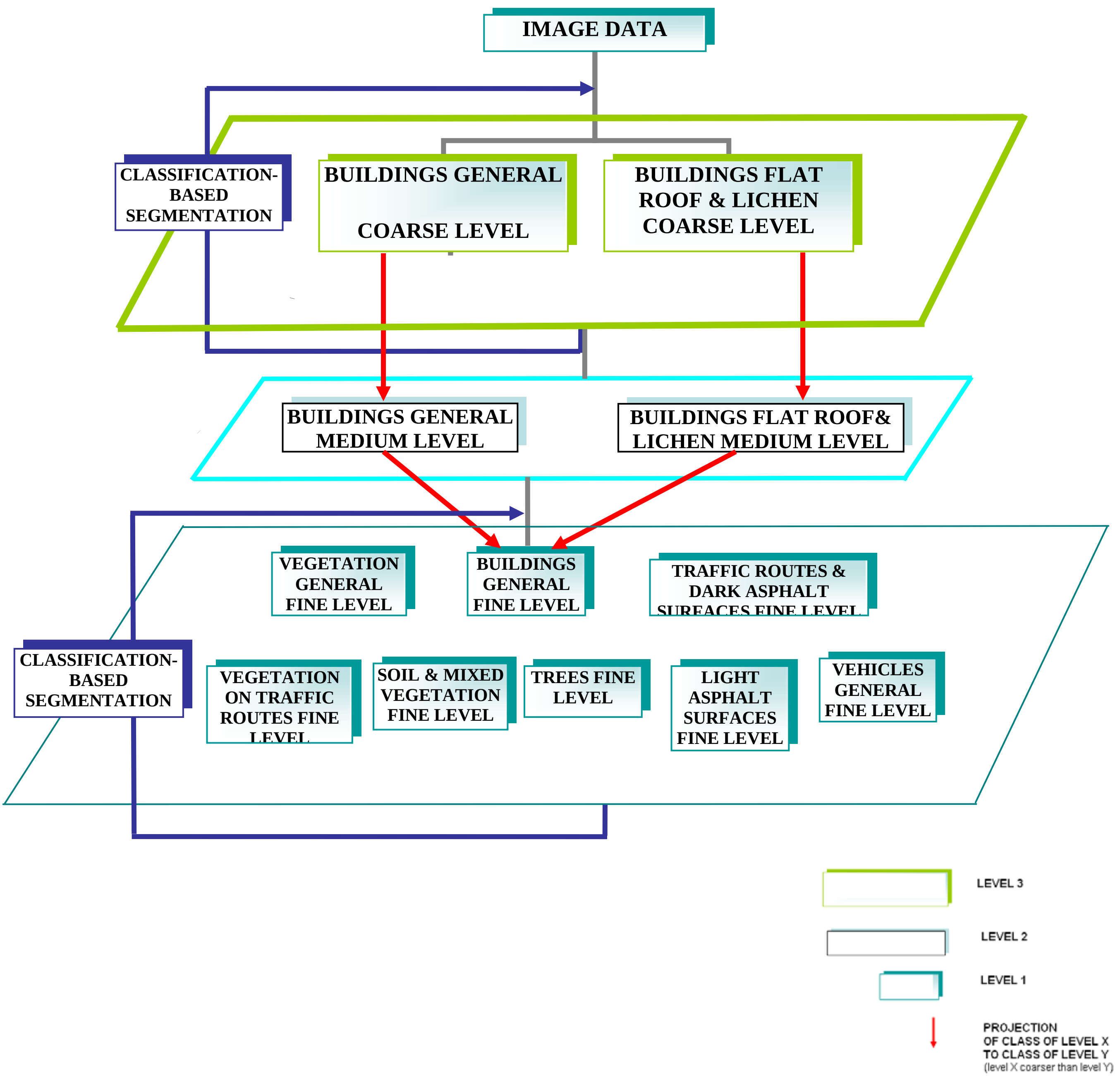
Where *d* is the distance between sample object *s* and image object *o*, $v_f^{(s)}$ the feature value of image object for feature *f*, $v_f^{(o)}$ the feature value of image object for feature *f* and σ_f the standard deviation of the feature values for feature *f* (Definiens-Imaging, 2002).

Focusing to recognize the buildings from other objects above surface of high altitude in the coarser analysis level, two classes were created for buildings with narrow description limits to avoid confusion of classes and of buildings' boundaries. Additionally, a first definition of the asphalt and soil surfaces was attained. In every class description the less possible features were used, so as to provide a prompt and apparent result of the combination that would be produced. Particular attention was drawn to the descriptions structure, so as not to insert many class-related features that would raise the probability of creating circular dependencies and thus the uncertainty in defining the classes.

3. Results and Discussion

Three analysis levels were formed for serving the aims of this study. The objective was to classify the majority of large objects in the coarse and medium level, in order to project the result in the fine level and by subtracting these entities from the scene to identify the objects in question, namely the vehicles.

Figure1 Schematic representation of the classes' hierarchy of all analysis levels of the object-oriented methodology.



The coarse segmentation analysis level (level 3) was formed by two approaches. Firstly, the top-down approach was applied in the principle that the representation of significant information is attained by significant conceptual objects and their interdependencies and not by individual pixels (Martin Baatz et al., 2001). As the top level of the segmentation, its segments-objects define the limits of all lowest levels. The main objective was to identify the large surfaces of buildings and aside to recognize vegetation, soil and traffic arteries, so as to set their boundaries in the finer segmentation levels. As the man-made structures have smooth borders, the maximum value was assigned to the smoothness criterion so that the segments-objects result with smooth borders.

Notwithstanding the mindful segmentation and classification, contour zones at the buildings borders with objects that included various classes, such as soil, vehicles and vegetation with shadows, were created, due to the different spatial resolution of multi-spectral and elevation data. In order to avoid these objects misclassification, the feature of mean difference of DSM LEL to scene was added in the description of the buildings. The DSM LEL contains information for the lowest edges of the impervious objects that the last laser pulse records and for the soil below the pervious objects, such as tall trees sparse leafage, thus a subtraction from all the entities of the image would result to tall large surface objects with more precise boundaries.

To enforce further the buildings' classification of the coarse level so as to project and use the results to the finer analysis levels, a classification-based segmentation was applied. In this bottom-up approach, all adjacent objects that represent the same land use, and thus characterised by identical structural units, as well as the objects that partially belong to a identical structural units, were merged and formed new segments-objects. Another classification based on the newly merged segments was effectuated, concluding to a better defining the buildings.

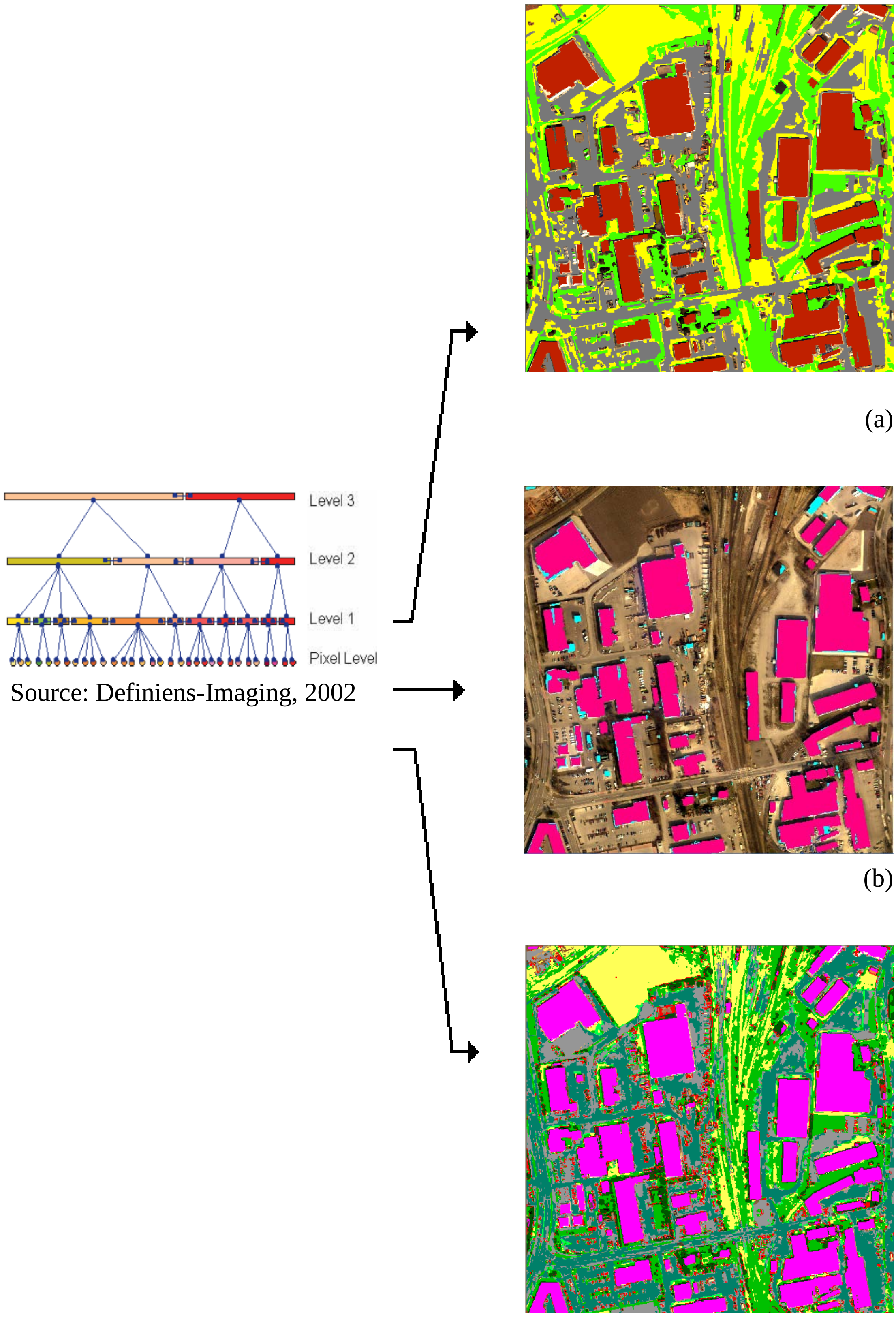
The medium level (level 2) was obtained by the top-down approach. As this level is of medium analysis, small objects such as vehicles, fine or sparse vegetation, cannot be classified accurately. Consequently, the focus was set on classifying unclassified segments of buildings and thus create elongated segments with smooth borders. By adding in the class description the attribute not mean nDSM, classification of lorries as short buildings was avoided.

The fine analysis level (level 1) was the result of a top-down approach. Four classes of buildings from the coarse and medium analysis levels were projected to this, so no further attempt to re-classify buildings was made. Because of the small size of segments-objects, the accurate identification of low-bushy and high-arborescent vegetation, sparse vegetation, soil, roads, light and dark asphalt surfaces was rendered possible. Given the constrained size of the objects that is aimed to recognise, namely the vehicles, and to prevent misclassification of certain parts of them, the probability of resulting with segments of mixed land uses was mitigated by setting a low value as scale parameter. Due to the elongated shape of vehicles and to the non-existence of specific spectral signature, but counting on the fact that the classification of objects of classes that possess specific range in the spectral feature space, the same value was assigned to both the colour and the shape criterion, so as to derive objects with similar land uses, smooth and elongated borders.

For the emergence of surfaces with low altitude, such as vehicles, without interjections from the adjacent arborescent vegetation, a higher value of weight was assigned to the DSM LEH slope comparing to DSM FEH slope. The choice of these DSM after the imposition of the slope edge detection filter is due to the need of altitude information even at the borders of the objects. The last echo DSM was selected because represents the lowest edges of impervious objects that the laser beam can reach, and the ground beneath the pervious objects, without any reflections of atmospheric particles that would plausibly confound the vehicles' classification in this fine analysis level of small segments. The reason for selecting the DSM FEH is because of the fact that the specific elevation model is consisted of the highest layers of pervious and impervious objects, namely sparse or dense leafage of arborescent vegetation. In the nDSM a weight was assigned, in consequence of the fact that depicts the objects above ground with their approximately actual values and it is more manageable in applying thresholds. Furthermore, the possibility of misclassification due to the contours that were observed near the buildings' borders because of the different resolution between multi-spectral and elevation data, where segments-objects with vehicles under shadow and bushy vegetation, is mitigated.

The formation of the vehicles' class description was based in the observation that the high reflectance, namely white, silvery, and the red and yellow vehicles displayed values of NDVI between 85 and 100, whereas the low reflectance vehicles, namely green, blue, black, ranged between 101 and 117. In addition to the expected values for the mean height of small, medium and SUV vehicles (approximately 1.20m to 1.80m), values between 1.50m to 3.50m were observed corresponding to vans, lorries (mainly of white colour), storage containers, justified by the fact that the study area is an industrial zone. The low observed values of mean height (0.35m – 1.5m) correspond to the front and rear parts of vehicles of the abovementioned classes. The final classifications of all levels and details of the fine level are following (Figure2, Figure 3).

Figure 2 Objects' network hierarchy of dataset 2 for segmentation level: (a) 3, (b) 2, (c) 1



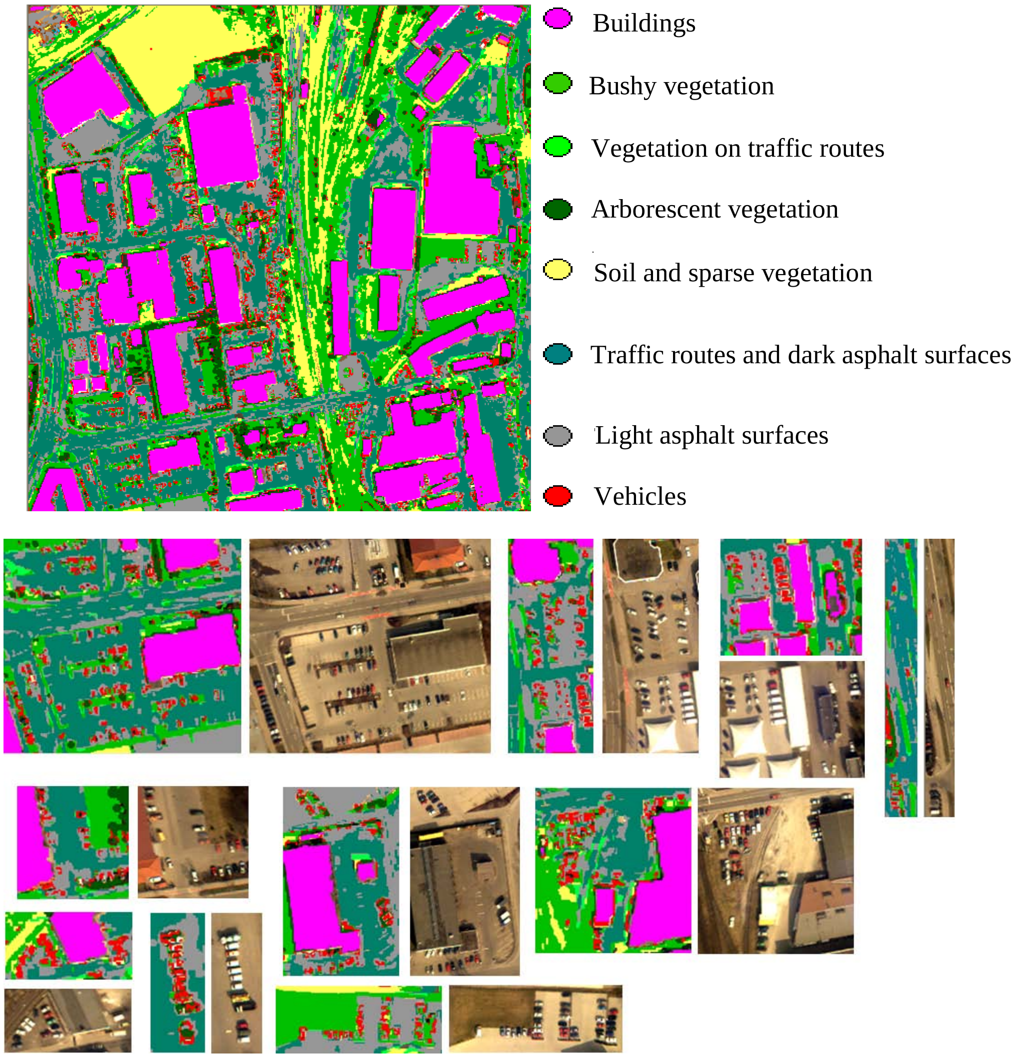
Source: Definiens-Imaging, 2002

(a)

(b)

(c)

Figure 3 Final classification of fine analysis level and details of vehicles classification in comparison to natural colour composite RGB 321.



3.1 Accuracy Assessment

The accuracy assessment was effectuated with the error matrix based on samples method. The samples were selected based on photo-interpretation experience and were assigned to the corresponding classes that were created during the classification processes. Based on the error matrix that was computed, it is observed that for the vehicles' class 190 segments-objects out of 233 of the samples that were assigned to this class, had already been classified to the right class. Given the size of the objects in question and the absence of a spectral signature, their classification is very adequate. The value of kappa index of agreement (KIA=0.855) and of the overall accuracy (0.9) justify the reliability of the classification, hence the fact that the classes were correctly describing the objects and that in particular the vehicles' classification was rendered successful.

4. Conclusions

In the object-oriented analysis, with the fuzzy logic syntax rules the precise recognition of objects is rendered more accurate and the identification of misclassified objects more evident, as for each object its assignment value for each class is computed. Furthermore, a reference study object carries spectral and geometric features that are employed for structuring rules for classes’ description, in which may be classified via the given spectral, geometric and newly formatted relative features, based on relationships between objects of the same, coarser or finer analysis level. Thereby, a database is created that can be used with datasets of similar environment, without important adaptations of the features’ range in the data, as during structuring them, the rule of not restricting excessively the attributes’ range according to the fuzzy logic of object-oriented analysis, imposed the creation of an objective and more global applicable database.

For that reason, a general definition was given to the class description of vehicle, based on common features of various vehicles’ types, so that with its implementation to be aligned with any dataset of similar resolution of industrial or urban areas with few alterations to the features’ ranges, and to precise identification and classification. Nevertheless, with a DTM of higher resolution that would not contain surface’s exacerbations or assign inaccurate altitudes to objects, the extracted information and classifications would be correspondingly more accurate.

The classification of objects with large surfaces of various land uses in the coarse and medium analysis level, and thus their elimination from the fine analysis level, reduced significantly the research area for vehicles and contributed to their classification. The high classification accuracy of the level is due partially to the précised definition of classes’ description, both of the level in question and the coarser levels. The misclassifications that occurred in the principal class of interest for this study, the vehicles’ class, were concerning vehicles that were located near objects assigned to the classes of vegetation and soil. The reason could be lying in the overlapping of ranges in common features. In particular, the random high elevation of surface and of bushy vegetation has similar values to the height of parts of certain vehicles’ types. In addition to that, the high values of NDVI in vehicles with low spectral values (i.e. black, blue) impeded the precise definition of all vehicles and of their types.

The logic behind the description of the vehicles’ class was based on the observation that the high reflectance, namely white, silvery, and the red and yellow vehicles had NDVI values between 85 and 100, whereas the vehicles with low reflectance, such green, blue, black, ranged between 101 and 117. In addition to the expected mean height values for the small. medium and SUV vehicles, namely approx. 1.20m-1.80m, values between 1.50m and 3.50m were emerged that corresponded to vans, lorries and storage containers, as the study area comprises also an industrial zone. The low height values, 0.35m to 1.5m, are justified as representatives of the front and rear parts of vehicles of different types.

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