Change Detection for Urban Spatial Databases Using Remote Sensing and GIS

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ABSTRACT

The aim of this study was to establish a preferred methodology for updating of the spatial database and monitoring the changes of a settlement in Tanzania. In summary, change detection problems can be viewed as the consequence of an increased desire for up-to-date information about the development and changes in a GIS environment to guide urban planners, urban decision-makers, and managers. Two methods that have been used for change detection are: semi-automatic change detection using on-screen digitizing and digital classification and segmentation methods.
On-screen digitising of changes shows that (as a pilot study covered only one aerial photograph) this method is fast, convenient, and (depend to the application) complete.
The result of segmentation and classification for finding the changes in the settlements Dar Es Salaam, shows 73% accuracy when the result of on-screen digitizing is used as a reference map for evaluation and by using existing knowledge such as roads and object geometry contained in the GIS database. Classification and segmentation can be used to derive information from an aerial photograph. The nature, variety and usefulness of such an information would have to be considered according to the project at hand, i.e., the structure of the area, the type of available aerial photograph, and the type of information to be extracted.

1 INTRODUCTION

In Developing countries new expansion due to development of unplanned area and urbanisation causes maps to become out-dated rapidly. Therefore, there is a need to revise old maps using a fast, efficient and effective method.

The problem addressed by this study is the lack of up-to-date and correct information about the development and changes of unplanned areas in Dar Es Salaam to guide urban planners, urban decision-makers and managers. Estimation by the City Council of Dar Es Salaam (UNDP, 1992), indicates that approximately 70 percent of the population live in unplanned settlements. These settlements are vast in extent and their population grows so fast that traditional data collection, processing and analysis techniques cannot provide planners and decision-makers with a correct view of them. The time interval between the production of the first map with the last map of a series may be too long. As a result a lot of new changes may have occurred again. Traditional map production processes are inadequate for this situation.

To revise an old map, it is necessary to detect the changed object in the area. An old map, and old and new aerial photographs are important basic materials for change detection. There have been a number of processes that use analogue aerial photographs for change detection. An example is plotting the changes with a mechanical stereo-plotting machine. But these processes are time-consuming, laborious, and, consequently not economical. Finding a more appropriate solution to this problem has become a genuine challenge. However, because of the possibility that now exists to scan analogue aerial photographs, it is possible to utilise them in a more efficient way. This study has shown how digital aerial photographs can be used to maintain the spatial database and update maps and the relevant information for urban planning in a faster, cheaper, and more convenient way.

2 DESCRIPTION OF THE METHOD

Before extraction of new data from the new aerial photograph (1994), it is worthwhile to compare the existing 1992 aerial photograph with the digital spatial database which has been produced from that photo. The reason for doing this is that the 1992 digital data will be used as reference data and the quality and accuracy of the source data should be ascertained before using it for further processing. This was done by overlaying the aerial photograph on the digital data and comparing some of their details using visual interpretation. (Darvishzadeh, 1997)

2.1 Visual Change Detection

In Figure 1 the methodology, which has been used in the experiment, is illustrated. In this approach, after scanning of the new photo, georeferencing, enhancement and other necessary corrections were done. Then the geo-corrected photograph was overlaid with the old digital data and changes detected using on-screen digitizing. In this case the detected changes were incorporated in the existing digital data. The following sections describe the procedure and the final results.

2.1.1   Scanning of Photo. An oblique colour aerial photograph of 1994, which was taken with a 35-millimetre camera, was scanned as one band for conversion to digital format. As the scale of the photograph was almost 1/2500, a resolution of 150 dpi (dot per inch) was selected, which gives one pixel for every 40 centimetres on the ground.

2.1.2   Georeferencing. After conversion of the image to the ILWIS program, the next step is georeferencing in order to bring the image to the coordinate system of the 1992 digital database. This is very important, as for registration of the image with the digital data they have to originate in the same reference. In the georeference module of ILWIS, 14 well distributed control points in the image and the corresponding control points in the digital data were selected. A projective transformation was used with a sigma of 2.38 pixels (0.95 meter), which is acceptable regarding to the scale of the digital data and photograph.
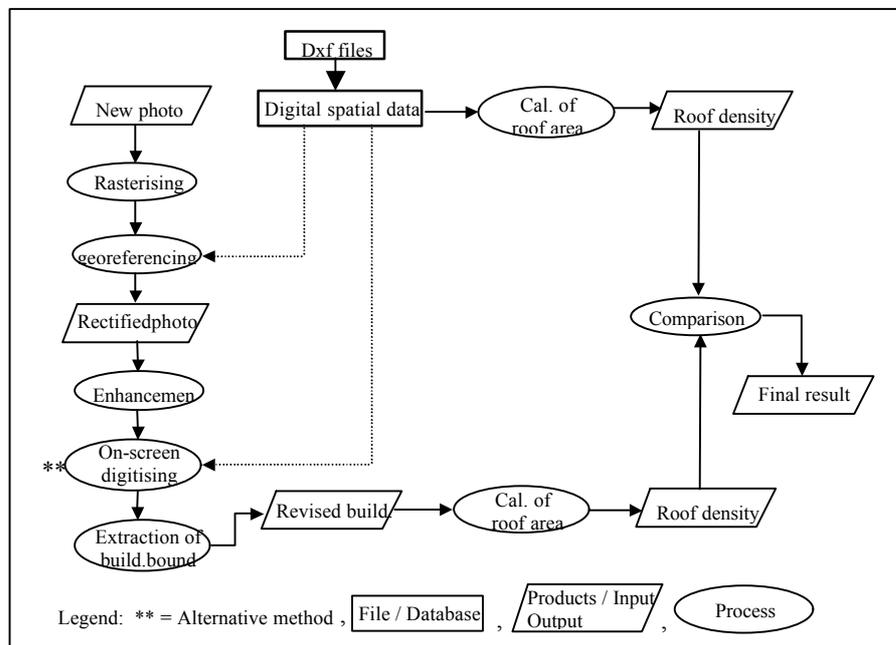
Figure 1. An overview of the visual change detection approach

2.1.3   Overlaying & Change Detection. After georeferencing, the aerial photograph and selection of a part of roof layer (which falls in the same area of photo) from the digital data, they were overlaid together. As a result the buildings which were somehow a change recognised.

In ILWIS, having the aerial photograph as a backdrop image, with overlaying the buildings roofs, the changes were on-screen digitized in a new layer and the digital data has been updated (see Figure 2). Table 1 shows the result of change detection and the number of houses, which is detected.

In The Area Of Photo	Old Data (1992)	New Data (1994)	Difference	
			absolute	relative
Number of Houses	1039	1108	+69	6.6%
Roof Area (m^2)	76000	80126	+4126	5.4%
Housing Density (building / ha)	35.8	38.2	+2.4	6.7%

Table 1. Comparison of old and new data in terms of roof changes
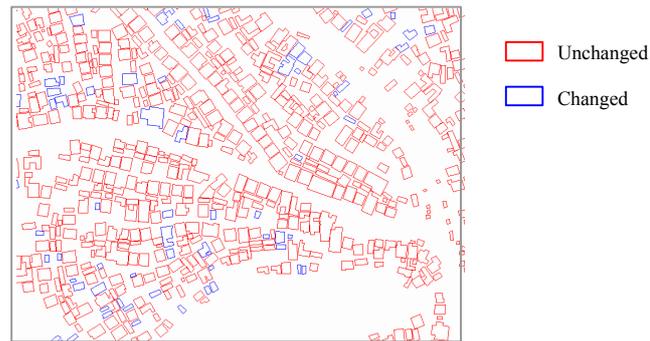
Figure 2. The changed and unchanged roofs in the area

2.2 Digital Change Detection

In this approach, after scanning of the new photo, the same procedure for making the geo-corrected image as in section 3.2 was followed. In the later stage, after rectified photo registration, classification and segmentation were used to extract roof changes, using existing knowledge contained in the GIS database. The final result (detected change) will be compared with the result of on-screen digitized data. Figure 3 illustrates this approach.
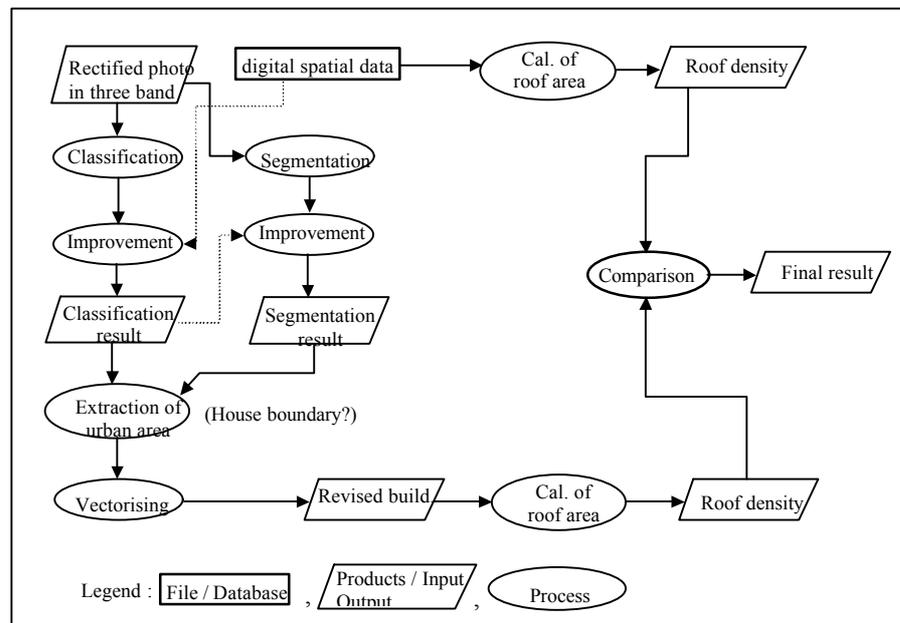
Figure 3. An overview of the analytical approach

2.2.1   Scanning Photo & Georeferencing. A similar procedure was used as that explained in sections 3.2.1and 3.2.2 with the exception that the aerial photograph was

scanned and processed multi-spectrally. A resolution of 150 dpi was chosen to have the same accuracy in the source data as in section 3.2.

2.2.2   Test Area and Data. For the next steps in this approach, three subsets were selected from the georeferenced images. The subset images consist of 520 lines and 500 columns, almost covering the middle part of the aerial photograph (an area of 41600 m^2). Classification and segmentation was done only for this part. Figure 4 shows the colour composite of the subsets for the test area.

From the updated (1994) layer of the digital data (updated roofs of buildings) that was detected in section 3.2**,** the test area was selected (reference map). The boundary of one of the subsets was identified and only the roofs, which would fall, in that area were selected. This data will serve two purposes:
1.   Knowledge acquisition from existing GIS (e.g., roads) for the knowledge based classification (improvement)
2.   Evaluation of the classification and segmentation results for extraction of roofs.

2.2.3   Pixel Classification. The pixel classification was performed by a standard maximum-likelihood classification using the three bands of the scanned aerial photos. The updated roof map guided the classification. The training data which was applied for supervised classification comprises the following 17 classes: roof1, roof2,…., shadow, and trees. The mean vector and covariance matrix of the seventeen classes was determined from a total of 150 to 300 samples per class. Figure 5 shows the result of the classification.

Figure 4. Study area   Figure 5. Classification result

After classification, all the roof classes were combined into one class (roof) and all the shadows and trees into another class (green). There also exist another class, which consists of unclassified pixels. Since there was no information about this class, it is named others (see Figure 6).

This classified map was subjected to accuracy assessment. The accuracy assessment was done by means of a confusion matrix and the overall accuracy (expressed as the percentage of correctly classified pixels) was computed. The overall accuracy of the classification result was assessed by a cross tabulation of the rasterized updated roof map (reference) and the classified map (see Table 2).

Reference map		Classification results		Acc.
		roof	others	
	roof	84646	33973	0.71
	others	58523	82858	0.59
Overall accuracy = 64.42 %				

Table 2. Confusion matrix when reference map was crossed with classified roofs

However, classification of remotely sensed imagery is effected by e.g. isolated and mixed pixels and spectral confusion of land cover types (Abkar, 1994). Therefore, in the majority of cases, classification based solely on spectral observation is not sufficiently accurate for extraction of the roofs, especially in this area where reflectance of the road and bare soils is very similar to the roofs. Consequently, no samples were taken for roads and bare soils. This means that a lot of roads and bare soils will be classified as roofs. For the roads this is not a problem, because we know where the roads are from the digital database. For the bare soils the situation is different; we have no prior information about them. This problem can not be resolved by considering bare soils in the classification. If so, the opposite case will happen that means many of roofs will be classified as bare soils.

1st-stage of classification improvement**:** As a result, existing knowledge from the digital database (e.g., roads) was used to improve the result of the classification. Roads were extracted from the digital data, rasterised and combined with the classified map and the roof map (reference). The overall accuracy of this result is shown in Table 3.

2nd-stage of classification improvement: The segments in the final classified map (1-stage) that are unclassified with a size of less than 5 pixels were detected (see Figure 7) and removed (converted to roof class). In Table 4 the overall accuracy of this result after this stage of improvement is shown.

The selection of the threshold (5 pixels) was based on two criteria:
1. The hypothesis that there are no roofs smaller than this threshold (0.8 m^2).
2. Choosing a larger threshold will affect opposite in the accuracy result. In fact, first only the segments which are unclassified and their number of pixels is one were removed. Then those which their number of pixels is two has been removed (added to roof class). The same was done for three and four pixels. When this number changes to five the accuracy will suddenly come down instead of going up.

Reference map		Classification results			Acc.
		roof	Road	others	
	Roof	84646	0	33973	0.71
	Road	0	30411	0	1.00
	Others	43438	0	67532	0.61
Overall accuracy = 70.23 %					

Table 3. Confusion matrix when updated roofs (reference map) with roads was crossed with classified roofs plus roads
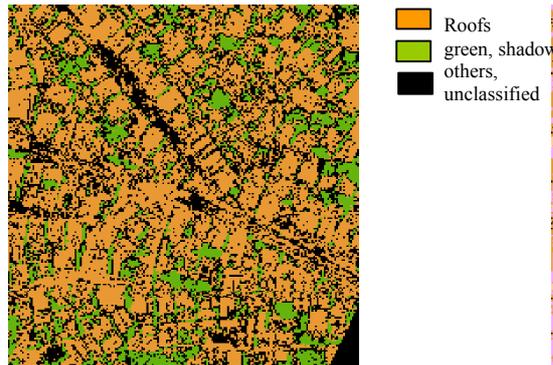
Figure 6. Combined roof classes with green areas and shadows on roofs were detected

Roofs
green, shadow
others,
unclassified

Figure 7. classified result when segments segments with number of pixels less than 5

Roofs
roads, soil
others,
unclassified
No of pixels < 5

Reference map		Classification results			Acc.
		roof	Road	others	
	Roof	85270	0	33349	0.72
	Road	0	30411	0	1.00
	Others	43736	0	67234	0.61
Overall accuracy = 70.35 %					

Table 4. Confusion matrix when updated roofs (reference map) including roads was crossed with the improved classified result

The explanation for this is that, although there are some segments on top of the roofs, which are unclassified and have five pixels or even more, there also exist some misclassified roofs that have the same situation. By adding to the threshold the area of the misclassified roofs also will increase. So the accuracy, instead of going up, will come down. The final classified map after the second stage classification is displayed in Figure 8.

Roofs

roads, soil

green, shadow

others, unclassified

Figure 8. Final classification result

Figure 9. Segmentation result

2.2.4   Quadtree Segmentation. Human image vision generally tends to divide an image into homogeneous areas first, and will characterize those areas more carefully later (Gorte, 1995). Applying this approach to digital image analysis leads to segmentation, which divides the image into segments that correspond to objects in the terrain. The

success of segmentation depends on the availability of: high resolution imagery in such a way that the relevant objects are represented by a significant number of pixels, powerful hardware, and an efficient implementation regarding the size of the remote sensing images (Gorte, 1998).

The segmentation program uses a multi band image (in this case 3 bands) as input and gives one segmentation as output. Moreover, information, like object locations, sizes and perimeters can be retrieved (readers are referred to technical report, experimental quadtree software, Gorte 1995). In this study the threshold was chosen by trial and error. The result of this segmentation is illustrated in Figure 9.

This result contains many small segments (noise) and mixed pixels. To remove all these the segments which their number of pixel is less than ten have become zero (see Figure 10), meaning that, all the objects with an area less than 1.6 m^2 will be deleted. Although by doing this some information may be lost, but those information is of no interest in this study as it is here supposed that a roof has at least an area of 2 m^2. Further improvement of this result was achieved by the segment-based classification, which is described as follows:

2.2.5   Segment-Based Classification. The aim of segment-based classification is to determine the class (label) of a segment (polygon), of which the geometry is contained in the segmented map using the above segmentation program. Therefore, the pixels within the polygon are identified from the classification result and the class of the polygon is determined from these pixels.

The following steps were taken to arrive from a pixel-based to segment-based classification: First the georeferenced image is classified using per-pixel classification resulting in a label per-pixel. The segmentation result has been Area Numbered to effect distinct area numbering; connected raster elements with the same value belong to the same segment. The output map from Area Numbering, was superimposed (crossed) with the final classified map in order to get the statistics of pixels within each segment. Subsequently, a frequency Table was established to determine the label of each segment. Then the most occurring (predominant) class label for each segment was calculated (using the Aggregation function) and assigned to the segment (including the unclassified labels).

The classification accuracy was assessed by comparing the output of the segment-based classification with the updated roof map (reference), by calculating confusion matrices and the overall accuracy. This result is presented in Table 5.

Reference map		*Classification results*			*Acc.*
		roof	Road	others	
	Roof	87939	0	30680	0.74
	Road	0	30411	0	1.00
	Others	38654	0	72316	0.65
Overall accuracy = 73.33 %					

Table 5. Confusion matrix when reference map (updated roofs) including roads were
crossed with improved segmentation including roads

Figure 10. All the small segments
With an area of less than 1.6 m^2
are detected

Roofs
roads, soil
green, shadow
others,
unclassified
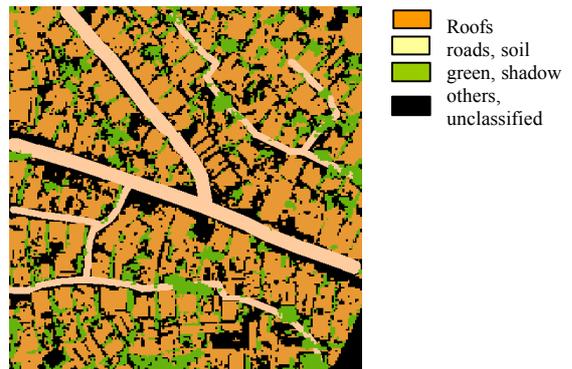
Figure 11. Final result of segmention
after using classification for
improvement

3 CHANGE ANALYSIS

The segment-based classification result was used to analyze the remaining differences between the old roof map (1992) and the roofs as determined with the segment-based classification (as it serves as the best result). The implementation of the segmented-based classification method resulted in a final map, which is presented in Figure 11. This result was used to derive the changes. For this reason, the final result of image segmentation (see Figure 11) was subtracted from the old (1992 roofs) data (see Figure 12). In the ideal case, the remaining parts of the subtraction should be only the changes. The result of changes found in the on-screen digitizing was overlaid with that result (see Figure 12). Visual analysis of this result shows the following types of error:

1. Existing error in the boundaries of roofs. As seen in Figure 12, there are a large number of small areas (Slivers) indicating errors along the boundaries of roofs. This incorrect classification can be largely explained by spectral confusion and incorrect referencing of roof segment geometry.
2. Existing thematic error in the old roof map (1992 digital data) which served as ground truth. Good examples of this type of error are the *detected changes* shown in Figure 12.
3. Error due to spectral similarity of roofs with e.g. roads, soils and the surrounding environment. The remaining unclassified and misclassified segments can be explained by this type of error. This type of error, can be seen from the visual interpretation of Figure 12 (large areas). This is an inherent problem of spectral classification and segmentation.

Figure 12. Derived changes from on-screen digitizing overlaid with changes from segmentation

4 CONCLUSION

The aim of this study was to compare the changes derived from on-screen digitizing with extracted changes by means of classification and segmentation. Although the result of on-screen digitizing had a better accuracy and completeness, it should be kept in mind that the knowledge and intelligence of an expert has been applied. In this case study, the time used for on-screen digitizing was less than for classification and segmentation but this may not be the case in a production environment. In the case of dealing with a bigger database it is obvious that on-screen digitizing may need more time. For classification and segmentation, once the method is developed, is much faster. However, a compromise may be made between the cost of achieving high levels of accuracy and the need for rapid change detection. Classification and segmentation may give a better result where the buildings are larger than those found in this photo area. The result of segmentation and classification could be improved by adding extra knowledge, for example adding some information about the shapes of the roofs or their textures (usually new buildings because of the new materials have different reflectance). Also this result can be improved by the accurate spatial registration of the image, which is possible through making an orthophoto.

Therefore, Scanned high resolution aerial photographs could play an important role in the various fields for spatial information gathering and map updating. They could provide the necessary data to create information for urban planners and decision-makers. The integration of remote sensing in a GIS environment makes it also possible to use knowledge on the history and the dynamics of urban land use to improve the image classification results.

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