MULTI-SCALE TEXTURE AND COLOR SEGMENTATION OF OBLIQUE AIRBORNE VIDEO DATA FOR DAMAGE CLASSIFICATION

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ABSTRACT:

Natural disasters are rapid and extreme events within the Earth's system. Since unheralded events are associated with widespread destruction and high mortality, there is a need for rapid, accurate and reliable damage information in the critical post-event hours. In practice, collecting such information is a challenge because of the interruptions in communication systems and access difficulties in affected areas. Oblique airborne video imagery, frequently captured by the media or law enforcement agencies, can provide valuable information in place of satellite images, providing critical information in a timely and low cost manner. However, oblique video imagery currently poses substantial processing, registration and integration challenges due to the nature of video imaging. These constraints cause scale variations of texture and colour information within and between video images.

This work addresses the classification of damaged und undamaged areas using texture and colour in video image segmentation. Specifically, this study investigates the use of multi-scale and multivariate texture based segmentations of oblique video imagery. Theoretically and computationally simple and efficient, we deploy Local Binary Pattern (LBP) and Variance measures to differentiate relative texture patterns of damage and undamaged areas. The approach investigated here was tested on video data acquired of the 1999 Kocaeli, Turkey, earthquake site. The following challenges in the use of video data are identified: (i) differentiating texture patterns of damage classes from undamaged regions using poor quality video imagery, (ii) automating such procedures for entire video sequences, and (iii) geo-referencing the results.

1. INTRODUCTION

1.1 Motivation

Disasters such as earthquakes, industrial accidents etc. are rapid and extreme events within the Earth's system, which cause substantial damage to human life and property. As a result of increasing densities of populations, infrastructure, and economic activities, vulnerability is higher in urban areas than in rural ones. Therefore, losses due to natural hazards are usually most severe in urban areas (Montoya, 2003). It is difficult to manage such sudden disasters without timely information. Reliable, accurate, and comprehensive information plays a vital role for the success of natural disaster management and damage assessment activities. Collecting such information is a challenge because of the interruptions in communication systems and access difficulties in affected areas (Ozisik and Kerle, 2004).

There are several methods of gathering damage information, ranging from ground surveying to acquisition from space and airborne platforms, each with their own limitations. However, it is important to collect damage information of affected areas immediately after the disasters in order to organize rescue, recovery and real damage assessment activities quickly and effectively (Mitomi et al., 2000). Non-calibrated oblique airborne video imagery captured by law enforcement agencies or media groups are often the first data available for gaining disaster information at an early stage (Kerle and Stekelenburg, 2004). Aerial video imagery is rapidly emerging as a low cost, widely used source for the management of many phases of a crisis or disasters such as surveillance, monitoring and targeting applications.

The goal of this work is to utilize video data taken directly after a disaster such as an earthquake to classify damaged and undamaged areas. A rapid classification may help in the decision process in emergency response. As damaged areas contain rich textural information, we deploy texture as an important feature. Texture has been used in the analysis of many types of images and it has been addressed and successfully applied in remote sensing studies in the past. Texture reflects the spatial structure of pixels in an image, and it is therefore indispensable in segmenting an area into meaningful units. Moreover, many previous studies have compared grey-scale textured features with their colour counterparts, concluding that adding colour information to texture measures increases the accuracy (Lucieer, 2004). To identify spatial objects with more detail and higher accuracy, texture patterns should be modelled at different scales (Ojala et al., 1996). Also, including multiple bands might improve segmentation considerably, as a combination of bands provides more spectral information for identification of different spatial objects. Hence, investigation of multivariate and multi-scale texture based segmentations of oblique airborne video imagery to extract damaged areas from undamaged regions is a promising approach in post-disaster damage estimation.

1.2 The Role of Texture and Colour in Image Segmentation

Object oriented analysis is becoming increasingly popular in remotely sensed image processing, since it can provide useful information about the object shape, texture and topological features. Texture and colour are the basic properties in image segmentation since they can represent any image through their variation. Texture is a fundamental characteristic of natural images, while colour plays an important role in human visual perception, providing better image understanding and visual interpretation (Xavier, 2002). Analysis of two-dimensional textures has many potential applications, such as in industrial surface inspection, remote sensing and biomedical image analysis. However, the segmentation of textured image areas is difficult, as textures in the real world are often not uniform, due to the variations in rotation, scale, size, and other visual appearances. The grey scale invariance and the degree of computational complexity of texture measures are the major problems in texture based segmentation. Randen and Husoy (1999) proposed the development of powerful rotation invariant texture measures that can be extracted and classified with a low-computational complexity.

Consequently, Ojala et al. (2002) presented a theoretically and computationally simple and efficient multi-resolution (or multi-scale) Local Binary Pattern (LBP) texture measure for grey-scale and rotation invariant texture classification. This operator allows for detecting uniform patterns in circular symmetric neighbourhoods at any spatial resolution and is very robust in terms of grey scale variations caused by illumination and intensity changes. Lucieer (2004) developed and tested a region growing segmentation procedure based on the multi scale LBP texture measure, to extract landform objects from LiDAR DSM data. Textural patterns with different scales were modelled by the extended texture measures $LBP_{c,j}$ and VAR_c with the multi-scale circularly symmetric neighbourhood sets. As multiple bands might improve the segmentation results and especially in the remote sensing imagery, Lucieer (2004) proposed a new multivariate texture measure as Multivariate Local Binary Pattern, (MLBPc) operator describing colour texture or texture in three different bands. It considers the spatial interactions of pixels not only in one band, but also between three bands. Hence, the neighbourhood for a pixel consists of the local neighbours in all three bands.

1.3 Scope of this work

This work focuses on the classification of damaged areas. To use the proposed classification efficiently in emergency response, one has to automate the process and also geo-reference the classified image areas.

1.4 1999 Kocaeli Earthquake, Turkey

The Kocaeli, Turkey, region has been developing into a modern industrial centre since the 1970s. On August 17, 1999, an earthquake of magnitude 7.4 struck western Turkey occurred along one of the world's longest and best studied strike-slip (horizontal motion) faults, the east-west trending North Anatolian fault. Over 75 miles of the fault ruptured generating 45 seconds of violent ground shaking at 3:02 a.m. (Harrald et al., 2002). According to the official government figures, the earthquake caused 17,479 deaths and 43,953 injuries, and left more than 250,000 people homeless (Figure 1). Most of the deaths and injuries in the earthquake were due to severe ground shaking causing the collapse of residential housing units, typically in three to six story reinforced concrete buildings with masonry infill walls. Although most buildings were damaged due to severe ground shaking, additional damage documented by Earthquake Engineering Research Institute (EERI, 2000), was due to fault rupture, liquefaction, coastal failures, and a small tsunami.

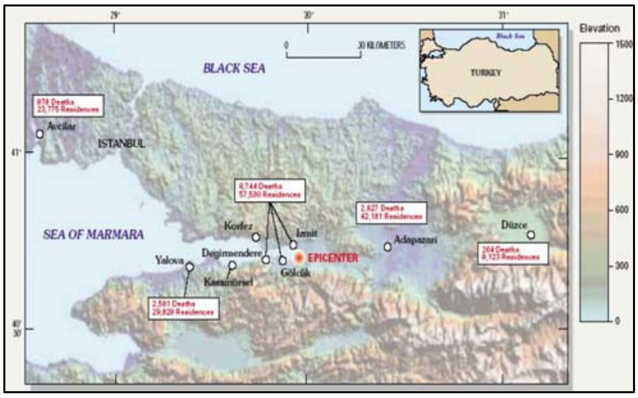

Figure 1: Damage to residences and human life of the major cities in Turkey (Babbitt and Groat, 2000)

2. DATA PREPARATION AND METHODOLOGY

The oblique viewing capability of video imagery provides the façade view of the damaged buildings. This can improve the damage estimation, as it allows a differentiation of the damage types and damage levels. A media agency, Show TV, acquired aerial video imagery immediately after the 1999 Kocaeli earthquake. A Betacam camera was used for image acquisition and total footage was approximately five minutes in length, with a resolution of 720 × 576 lines. It was typical television footage in that there were no plans to use the data in scientific applications. Consequently, the movement of the helicopter and zoom in/ out actions of the camera affect the quality of video images (Ozisik, 2004).

Data preparation and methodology applied included three basic components: pre-processing, processing and post-processing. Under the pre-processing stage, frame grabbing, image enhancement, and video mosaicing were performed, while visual image interpretation, multi-scale and multivariate segmentations were subsequently carried out. Finally, results obtained from texture based segmentation of different video images, which represent different scale texture patterns, were analyzed and evaluated by using derived damage classes from visual image interpretation (Figure 2).

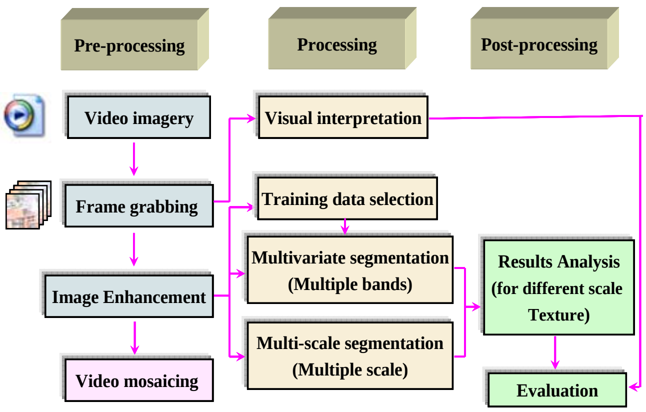

Figure 2. Methodology applied

Individual frames were extracted at the rate of 25 frames per second, which lead to 8625 individual video frames for total footage of around five minutes. Video data acquired by media agencies is typically low in quality due to the nature of currently used video technology. AstroStack [http://www.innostack.com] was used to improve the quality of the image. The idea behind this process was to restore some of the lost information, and to reduce overall noise from the series of input images, and to derive one noise free and more detailed image. Moreover, the actual damage classes derived from visual interpretation of oblique video imagery were used to evaluate the results from multivariate and multi-scale segmentations (Figure 3 & 4).

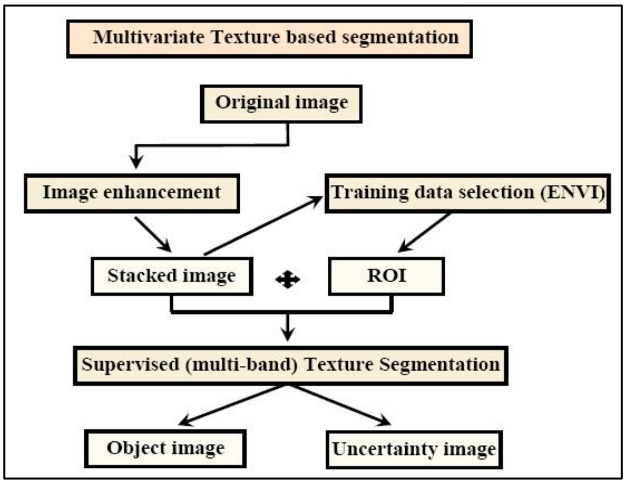

Figure 3. Multivariate texture segmentation

The three color bands of the enhanced oblique video imagery were used in this study to differentiate damaged areas from undamaged regions, and one original frame was used to select region of interests (ROI) for selected feature classes. Those two results were then fed into the supervised (multi-band) texture segmentation algorithm in Parbat (2004) to perform multivariate texture based segmentation, which uses different colour information or information from multiple bands.

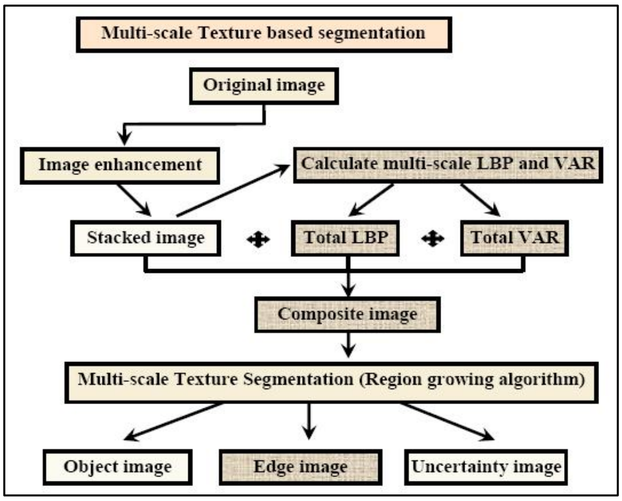

Figure 4. Multi-scale texture segmentation

The multi-resolution LBP algorithm developed by Ojala et al. (1999) provides a good platform to extract spatial objects from remote sensing images with different scales. The different values for a number of circular neighborhoods (*P*) and the radius from the central pixel to the circular neighbourhood (*R*) can be used to describe the local texture patterns at different circular radii. Similarly, in the multivariate texture segmentation three adjacent video frames were stacked and LBPs and VARs were calculated for a given range of radii (R=1 to 3). The total LBP and total VAR images of this given range were then stacked with the enhanced image as different layers, in order to create a composite image as an input for the region growing algorithm. The algorithm allows to calculate the thresholds by distance or angles and to select random seeds and number of adjacency. Finally, the segmented object image, the demarcated object edge image and the measured uncertainty for objects (uncertainty image) were obtained as a result.

3. DATA ANALYSIS

3.1 Image segmentation in oblique scenes – Test Cases

On one hand, the obliqueness of aerial video imagery supports the acquisition of detailed damage information in disaster damage estimation, providing façade information. On the other hand, however, the frequent changes in viewing angle and the perspective views hinder image enhancing and video mosaicing. However, this study mainly focused on improvement of damage estimation using texture based segmentation algorithms. Hence, it is worth to discuss the influence of obliqueness of video imagery in texture based segmentation. Its accuracy depends on the similarity of texture patterns in similar objects and the variation of texture patterns in dissimilar objects. The texture variation of features in turn depends on the shape, size, density and direction of texture patterns. However, the varying obliqueness and different viewing angles of video images can change the textural properties of the same feature classes in one image as well as in the subsequent images.

Especially due to the obliqueness of video imagery, the same spatial objects can appear in the image at different scales. We simplify the perspective distortion caused by the oblique view by a local scale. It is important to investigate the textural variation with respect to the scale differences using texture based segmentations, before testing the algorithm for real video images. Two different building walls (BW), roofs (BR), and collapsed (C) regions were extracted from the selected video images and degraded to derive their smaller scales. An artificial image with 256 × 256 pixels was created by joining them together. Training samples were selected in two ways, one from the larger scale and then the other from the smaller scale texture regions. The segmentation results from supervised multivariate segmentation are illustrated in Figure 5. Apparently the scale variation of the same texture patterns can be identified by the multivariate segmentation algorithm.

The texture patterns of similar objects can change in shape and size with respect to the different viewing angles and the distance of the objects from the camera. Thus the texture patterns, similar or identical in reality, can change in size and shape within and between video images. Although the texture patterns in collapsed areas are not considerably affected by the different viewing angles, a prominent effect can be found on other damaged and undamaged structures in disaster affected regions. Hence, it was important to investigate the effect of such texture variations on texture-based segmentations with different viewing angles before testing the algorithms for real complex video images. In order to create an artificial image (512×512 pixels) with the same texture pattern in different directions, texture patterns of undamaged building in different views were extracted from still digital images. To examine the changes in texture patterns without the influence of colour, a grey scale image was created from the original artificial image. Training samples were selected as windows and wall 1-4 to investigate the textural variation of walls in the different views (Figure 6).

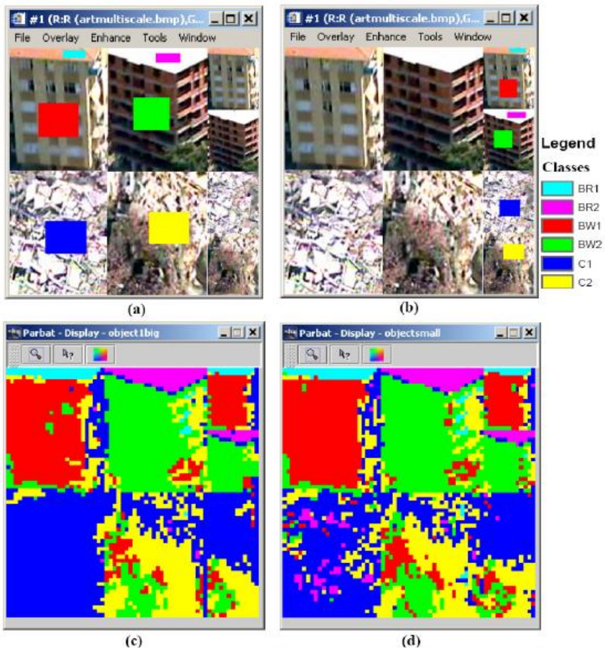

Figure 5. Multivariate segmentation of same color textures in different scale

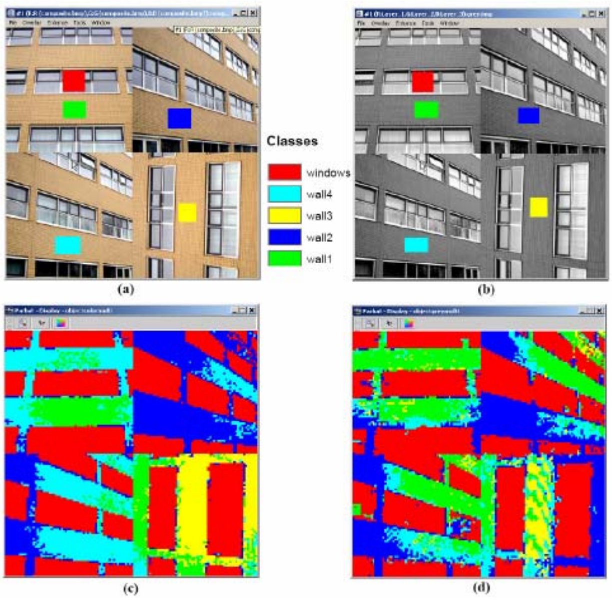

Figure 6. Texture and color variation of same object with respect to the different viewing angles

The segmentation results from multivariate texture segmentation illustrate a significant variation of texture in the walls with respect to the different viewing angles. Further, the same texture pattern in the same view is also changing with the distance from the camera to the desired texture scene. However, LBP is capable of identifying texture variations of one plane rotating through its centre point, since LBP is rotation invariant for monotonic images [See segmented areas in right with blue in Figure 6 (d)]. The misclassification of selected feature classes implies significant changes of texture patterns with the different viewing angles. The illumination changes with respect to the different views, affecting the colour information. Hence, the integration of colour information supports the multivariate algorithm to identify the same texture in different views as different. However, in disaster damage estimation to differentiate disaster affected regions from undamaged areas, such minor changes within the same texture in different views may be insignificant. This is because the changes in texture patterns between damaged and undamaged surfaces tend to be more substantial.

3.2 Supervised multivariate texture based segmentation for real video images

According to the segmentation results from the artificial image with natural texture patterns in the disaster area, it can be argued that the vegetation, sky, and water classes can be excluded from the original video image as top-down approach to distinguish damage areas from undamaged regions. This is because such classes are texturally and spectrally sufficiently different from the other classes which are relevant in damage estimation. Then, the resultant image will only contain the relevant information of disaster damage estimation. The training areas were selected as polygons for different types of selected feature classes to segment the desired areas in a bottom-up, explicit search approach. Some selected video images were segmented in order to define their selected feature classes. The values for number of circular neighbourhoods and the radius from the central pixel were chosen as 8 and 1 pixels, respectively (Figure 7).

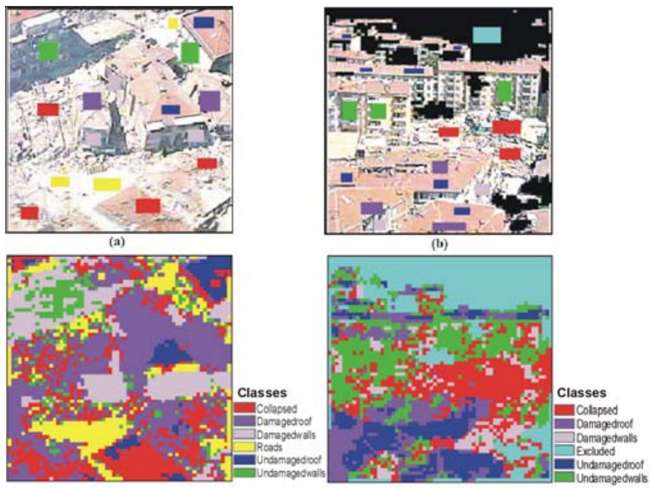

Figure 7. Multivariate texture segmentation for real video images

Better segmentation results for *vegetation* could be achieved since vegetation differs sufficiently from the other classes in terms of texture and colour. Basically, the *collapsed* areas were segmented with some road artefacts, because the smooth surfaces of roads and some collapsed structures provide high reflections, giving such areas high Digital Numbers (DN) for each Red, Green, and Blue band of the video image. The chimneys and structural changes of the roofs were identified as some small *collapsed* segments since they structurally deviate from the homogeneous *undamagedroof* texture pattern. Apparently the *damagedwalls* were segmented properly with some additional segments which were identified incorrectly due to shadows. As a whole, it can be visually interpreted that the *collapsed, damagedwalls*, *roads*, and *undamagedroof* were not well separable in the segmented image. The segmentation results were evaluated by overlaying them together with the areas identified for selected feature classes by visual interpretation (Figure 8).

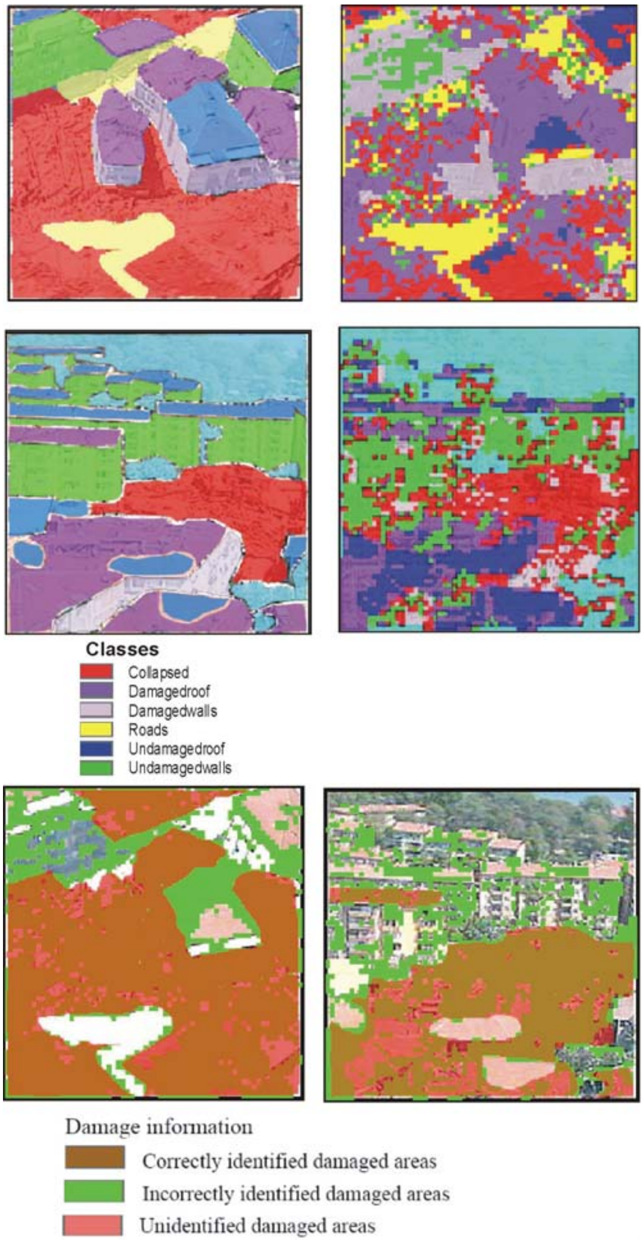

Figure 8. Segmentation results comparison with the results from visual interpretation

In order to check the damage levels which can be derived from aerial video imagery, and to assess the accuracy of segmentation, all collapsed and damaged classes were reclassified as a new class *Damaged*, while the other undamaged, roads, and excluded classes were renamed as *Undamaged*. The accuracy of the segmentation for damaged and undamaged regions was then analyzed using the segmentation results from visual interpretation. The segmentation results show that the multivariate algorithm is capable of identifying collapsed regions or detecting rubble from disaster areas, although it fails to detect intermediate and storey collapse. Some small objects on the undamaged roof such as chimneys, and some structural patterns on undamaged walls were identified as damaged. However, since the multivariate algorithm is only concerned with the textural and colour information of the video images and not with any geometrical characteristics and semantics, identification of soft storey collapse or slumped buildings is not an easy task, even with the façade information provided.

3.3 Unsupervised multi-scale texture segmentation for real video images

To identify structural patterns of spatial objects in disaster damaged area with more detail and higher accuracy, patterns should be modelled at different scales, which can be achieved with the use of different values for *P* and *R*. The larger scale neighbourhood set might fail to identify the patterns of structural damages, while a smaller scale has limitations to capture the patterns of large undamaged buildings etc. Hence, this study also investigated the suitable parameterizations of *P* and *R*. The segmentation approach was initiated by testing algorithm for an artificial image with natural colour textures extracted from disaster damage region. Afterwards, all the selected video images in the multivariate texture based segmentation were analyzed in order to check their improvement in segmentation by the concept of multi-scale.

The same enhanced video frames, which were used in multivariate segmentation of the different regions in a disaster area, were selected to test their improvement in disaster damage estimation with respect to the multi-scale texture segmentation. For every pixel in the selected image, texture measures were calculated for different number of neighbourhood sets, in order to select suitable values for *P* and *R*. The number of circular neighbourhoods was kept as 8, while changing the radius from their central pixels as 1, 3, 5, and 10. When considering the spatial objects in these types of video images, the suitable parameters were selected as 8 number of circular neighborhoods with 1-3 multi-scale radii. The segmentation results were visualised as an object image, assigning each object a number and classifying them into different colour classes. The object boundaries were extracted and overlayed on the original enhanced image in order to visualize the resulting segments on the real spatial structures (Figure 9).

When the results of multi-scale segmentation were compared with those of the multivariate approach, identified objects such as *buildingroofs*, *walls*, and some *collapsed* regions were free from misclassified artefacts. Basically, the multi-scale LBP algorithm is capable of identifying scale variations of structural patterns such as from small windows and small collapsed structures from large homogeneous roofs and roads. Hence, the damaged heterogeneous areas could be separated from the undamaged homogeneous regions. However, shadows and poor quality of video images caused restrictions in obtaining better segmentation results for disaster damage estimation. Overall, the multi-scale texture segmentation itself can not provide disaster damage information explicitly.

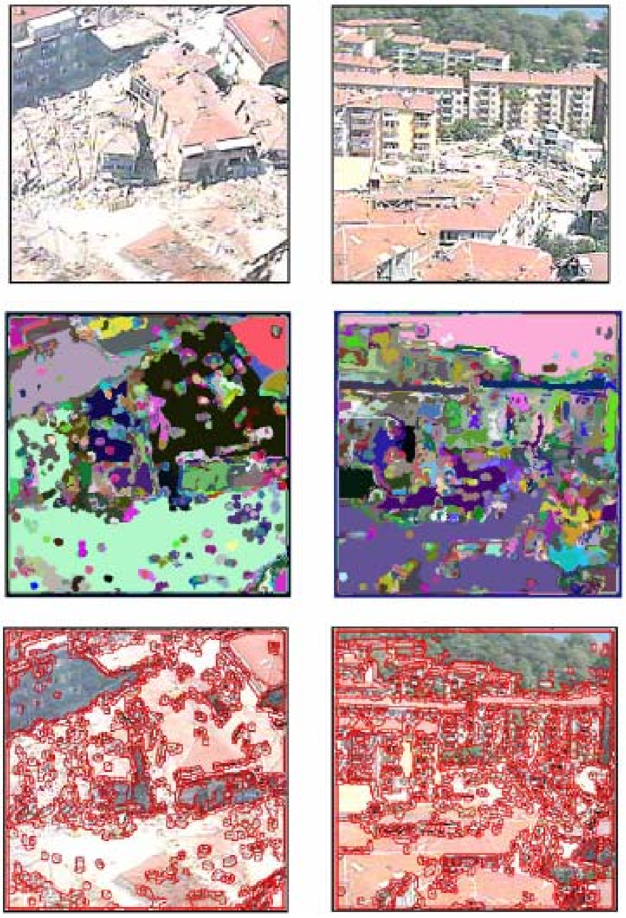

Figure 5. Multi-scale texture segmentation of real video images

4. DISCUSSION AND CONCLUSIONS

After testing the satellite and aerial video images for post earthquake damage assessment, Ozisik and Kerle (2004) concluded that oblique videos are a powerful tool to detect damaged areas, in terms of time requirement for data acquisition and amount of damage information. Moreover, the threshold-based video image analysis showed that the ability of detecting totally collapsed buildings with rubble rather than the other damage types, such as first storey or intermediate storey collapse. Nevertheless, in multi-scale texture-based segmentation the damaged and undamaged windows could be detected based on the shape of their structural arrangements. Hence, it leads to distinguish the intermediate and story damages of the high-rise buildings if the interpreter is capable of identifying it from a complex segmented video image.

It is advisable to use texture-based digital image analysis especially to delineate damaged areas from undamaged regions due to the textural differences between the two. However, in reality the presence of undamaged objects in the damaged regions, and of damaged structures over undamaged objects is not uncommon due to the sudden destruction caused by an earthquake. In practice the oblique airborne video images, as used in the Kocaeli disaster damage estimation, are still of limited value in terms of the quality of the video images, coverage of the disaster damaged areas, and the imaging nature, since they are disturbing the digital image analysis for accurate information generation. However, such limitations can be controlled up to some extent through a proper flight planning.

One of the main challenges in remote sensing classification is to derive land use classes from a classified image that in actuality represent different land cover types. The properties measured with remote sensing techniques are related to land cover, from which land use can be inferred, particularly with ancillary data or a priori knowledge. The multivariate and multi-scale texture based segmentations consider the texture and colour information of the damaged areas to extract the damage information, for example for collapsed, undamaged walls/ roof, damagedwalls/ roof etc. Thus, the fuzzyness of the concept of damage and level of damage with respect to the crisp texture based segmentation algorithms was the main challenge in this study. Hence, the selected training samples for each feature class may not be the best way to link the algorithm based on textural information with feature classes that are more based on semantic concepts.

The advantages and the limitations of using texture based segmentations of oblique airborne video images in disaster management and damage estimation have been discussed. It is apparent that for this approach to be successful, careful flight planning as well as appropriate image processing are required. Moreover, a range of concepts concerning the integration of texture and colour information for image segmentation using video images are still to be addressed. In order to find the level or the nature of damages, the changes of geometrical properties of objects in detail need to be further investigated. Furthermore the availability of auxiliary information plays a vital role for the accuracy of damage estimation and locating such estimated damages to the ground. Hence, a proper geo-referencing method needs to be introduced considering the nature of video imaging.

The spatio-temporal characteristics of oblique airborne video data were not extensively used in this research. Such redundant information was incorporated only in the processes of image enhancing and mosaicing although were not used in image segmentation process directly. However, using a better mosaicing approach and using mosaiced images in image processing, will facilitate the use of such redundant information. The multivariate and multi-scale algorithms were used separately to improve the disaster damage estimation in two different ways, by integrating texture/ colour and multi-scale texture information. Hence, if an algorithm can be developed to consider the texture in different scales together with the colour information, the results of damage estimation could be improved.

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