1. INTRODUCTION

After an earthquake, demolished structures have to be recorded in order to generate a map of buildings damage and property losses. In this respect, obtaining real-time or near real-time information of seriously damaged areas immediately after a natural disaster is extremely useful for executing efficient search and rescue missions. Remote sensing techniques either by air-borne or space-borne sensors were used in the last decades to detect, identify and monitor the impact and effects of natural disasters like earthquakes, landslides, tsunamis and floods (Li et al., 2010; Nolte et al. 2010). It has to be emphasized that the basic knowledge of remote sensing is essential to decide on appropriate technology in an emergency situation. To use appropriate imagery data one has to consider the spatial resolution, sensor type and action period, area to cover, etc. (Altan and Kemper, 2008; Kerle et al., 2008).

Automatic extraction of damaged man-made structures from images is difficult for many reasons. Space- and air-borne images, especially in urban areas, have a wide variety of structured and unstructured content. However, target buildings might be already identified using pre-event auxiliary data in desired format (e.g. building polygons). To determine the damaged buildings in the course of the damage detection from imagery data, evidence features must be collected which are detectable when comparing the pre- and post-event data. For this purpose, pictorial attributes like edges, texture or shadows can be extracted. The presence/absence of shadows in a pre/post event pair is a signal of a collapsed building (Turker and San, 2004, Vu et al., 2004; Turker and Sumer; 2008).

Texture analysis can be conducted for debris detection. Various approaches have been used to investigate the textural and spatial structural characteristics of image data for damage detection, including first and second order statistical features, wavelet transform, morphological descriptors, variograms and density or dissimilarity of edge pixels (Mitomi et al., 2001; Huyck et al., 2005; Rathje et al., 2005; Sumer and Turker, 2005; Shirzaei et al., 2006; Sertel et al., 2007; Gueguen et al., 2009).

3D information from intensity level matching or range data is also an important cue. Geometrical properties of buildings can be recorded from a digital surface model, which is extracted either from stereo images or laser scan data. Stereo or multiple images give reliable cues to infer 3D structures. Height differences to initial height, volume reduction rate, debris size, change of roof structure and inclination can be employed in order to assess building damages (Turker and Cetinkaya, 2005; Rehor and Baehr 2007). It is suggested that both image and object space cues should be exploited to perform more accurate change detection and classification (Rezaeian and Gruen, 2007; Rehor and Voegtle, 2008; Rezaeian and Gruen, 2011).

2. OVERALL VIEW OF OUR STRATEGY

We develop a system that automatically interprets data produced by aerial sensors before and after an earthquake in order to arrive at a detailed damage map quickly after the disaster. The research focuses on the interpretation of aerial images of urban areas, under the condition that prior information about building positions is not available. Given a...
set of aerial images of a city, the proposed system selectively applies image-understanding algorithms to recognize buildings prior to classifying the scene.

We aim to detect the points belong to the buildings’ rooftops and comparing these points before and after the earthquake in order to detect damaged points. In the proposed method, we deal with decision making for each single point of object space employing features extracted from segments in image space (Figure 1). Therefore, the goal is to detect and discern damaged points rather than extracting geometrical model of buildings. Within a particular area, the number and severity of the damaged points are translated to a damage scale. This area can either be a building rooftop or a district zone or even the whole city. Another aspect of the proposed system is to handle “uncertainty”, based on available information. This is accomplished through the selective application of algorithms to segmented fields in the data and combining their result in a Bayesian network. The network provides point-wise classification based on prior information of image segments.

Figure 1. The reasoning system will make a decision for given points (Pn) based on the collected evidences from corresponding image segments – (P1 is projected on different segments due to DSM errors).

3. AUTOMATIC DAMAGE ASSESSMENT

3.1 Line-based image segmentation

The goal of our segmentation algorithm is to partition the images of a city into a number of regions that correspond to surfaces in object space. Straight-line segments in urban areas can provide important information about the type (and number) of objects present in a local area of the image. We assume ideally each segment separated by a line. In order to form segments, a specific grouping technique that leads to closed polygons has been developed. This algorithm iteratively detects obvious and obscure straight lines and projects each line to a nominal plane in the world, based on the known camera parameters. Then, neighbourhood relations between two lines are tested and grouped into higher-level aggregate features based on geometric constraints such as colinearity, proximity, perpendicularity and parallelism. This allows constraints to be expressed in terms that are independent of the perspective projection for a particular image (Figure 2).

3.2 Features and cues extraction

The proposed system derives necessary and useful low-level information for each image segment in order to fuse related information. The introduced features are directly related to object and image spaces so that geometrical attributes are derived from DSMs - generated automatically - as well as imagery properties are extracted from the camera sensor (i.e. optical sensor). Based on this idea the following features are proposed:

Features extracted from DSMs

DTM and DSM data are used to derive general features as height and slope of the segmental surfaces. Comparing these data before and after earthquake can be conducted for detecting damaged points (Turker and Cetinkaya, 2005; Rezaeian and Gruen, 2008). For this purpose, each segment of the image(s) is projected down in object space using transformation functions and then those points of the DSM within the projected segment will be processed to estimate planar surfaces (Figure 3). Using normalized DSMs, the features such as average heights and tilting angles with
respect to horizon planes can be registered for each image segment. A trend-surface of a given order can be fit to any set of data, but does not guarantee that it is a meaningful or worthwhile model. It is necessary to compute measures of goodness of fit of the function to the data and to determine if the function components are statistically significant. Therefore, fitting planar surfaces to the height points, which project into each image segment, and computing the average height, tilt angle and goodness of fit results in DSM-based evidences.

Features extracted from images

Segments appearance could be another cue for our inferring system. The regions surrounded by long straight lines may indicate the undamaged buildings and are directly applicable to the inferring system. Moreover, those segments, which appeared as polygons with parallel sides, can be likely candidates for being rooftop segments. We propose an index to quantify similarity between extracted segments and such polygons. For this purpose, the histogram of edge pixels with respect to line directions is generated. The line detector has already generated the direction angles. A window with specified width (e.g. 10 degrees) moves on the histogram and computes the total number of pixels located about a specific direction. This quotient gives a positive number less than 1 and the number close to 1 indicates a polygon with parallel sides in two major directions. Also, we use the quotient of region pixels to perimeter that gives a measure of compactness.

As a result, for any segmented image, region boundaries are stored as 2D polygons, with attributes for colour range in the regions, greenness, compactness, and shape index (extracted from images) and trend surface information (extracted from DSMs).

3.3 Multi-view multi-modal knowledge based system

It is obvious that the results of a system for digital surface modelling can be corrupted by both the imperfection of measuring devices and matching algorithms. Additionally, the image segmentation may be imperfect and somewhere cannot reflect the polyhedral faces appropriately. All these influences add a certain amount of noise or uncertainty to the true and ideal values and we have to take uncertainty into account for practical applications. Using multi-images data together with statistical characteristics of grouped points, clustered within image segments, can lessen the impact of these effects.

The evidence policy is to select out the best relative features and discard the rest. We first exclude the segments with compactness less than one and then those with the best “trend plane” in terms of goodness-of-fit and tilt angle are selected for the decision-making procedure. All evidences ($\phi$) extracted from DSMs and aerial images have to be integrated through a ‘decision making system’ in order to detect buildings and then detect damaged ones. We started by establishing a naïve Bayesian network for building detection. The network is composed of six features as child nodes and one parent node ($H_a$, $H_b$: $Pn \in$ Building rooftop before/after earthquake). Adding a new node augments this structure. We called it “Features Conformity”. The idea is: corresponding features that are extracted from different segments while being closely similar should obtain more reliable evidence for the reasoning system. Hence, by adding the FC node (Figure 4) the network became circumspect about inferring with disparate features. A-priori knowledge, in the form of initial prior probabilities associated with each hypothesis, is used in the initial step. When no prior knowledge is available, equal probabilities are assigned to all possible states of the root nodes (i.e. $P(H = \text{True}) = 0.5$, $P(H=\text{False}) = 0.5$). In the hypothetical case where we know the correct class areas beforehand and base prior probabilities on these, we obtain an improved classification as compared to using equal priors. This prior knowledge is assumed to be supplied by an operator who is familiar with the site to be processed and is able to estimate the statistical distribution of the
object. After an earthquake, the number of damaged buildings for each damage grade can be estimated by using fragility curves, peak ground velocity and buildings density in the studied area. These values reflect user knowledge about each test domain, which can be applied by a prior probability. The results show that only minor modifications of the network prior class expectations across regions before and after disaster can allow the system to achieve an effective performance level. For this purpose, we can readjust prior probabilities before and after the earthquake considering information that may be derived from building characteristics such as construction class (e.g. wood-frame, steel-frame, reinforced concrete, etc.) age, height and so on.

4. REASONING SYSTEM FOR DAMAGE CLASSIFICATION USING BAYESIAN NETWORK

The main contribution of the previous part was to explore the use of Bayesian networks to combine various features obtained from DSM and imagery data to detect and extract man-made regions. Now, we can combine the results of before and after the earthquake for damage detection of man-made objects. To detect damaged points we propose a symmetric form of Bayesian network, including two parts for building detection before and after earthquake (H_b and H_a). The final section of the network is organized based on the perceptual concept of a damaged region. In this part, results of previous section are considered as input to estimate the final predicate (H_d, P_a is damaged). Moreover, the reduction of average heights (φ_2^before − φ_2^after) is used as well (Figure 4).

The standard deviations can be set regarding the DSM accuracies, which can be obtained by estimating checkpoints and/or taking sensor models and image scales into account. The probabilities Pr(H_b=True) and Pr(H_a=True) can be obtained from Bayes theories(Ben-Gal, 2007).

We perform hypothesis test that hr is discretized into intervals: hr < 1m and hr ≥ 1m. The conditional probability table is established (Table 1).

<table>
<thead>
<tr>
<th>H_b</th>
<th>H_a</th>
<th>hr ≥ 1m</th>
<th>H_d</th>
</tr>
</thead>
<tbody>
<tr>
<td>True</td>
<td>True</td>
<td>True</td>
<td>Dr: Dropped rooftop</td>
</tr>
<tr>
<td>True</td>
<td>False</td>
<td>False</td>
<td>U: Undamaged building rooftop</td>
</tr>
<tr>
<td>True</td>
<td>False</td>
<td>True</td>
<td>De: Demolished rooftop</td>
</tr>
<tr>
<td>False</td>
<td>True</td>
<td>×</td>
<td>C: Changed rooftop</td>
</tr>
<tr>
<td>False</td>
<td>False</td>
<td>×</td>
<td>N: No building</td>
</tr>
</tbody>
</table>

In this table, two levels of damage: Demolished (De) and Dropped (Dr) rooftops are defined. Moreover, undamaged area is divided to: Undamaged building (U) and No building (N) regions. The attribute known as Changed (C) can translate to “probable damage”. This attribute would be assigned when “H_b = True” and “H_a = False” and null hypothesis for height variation is not rejected. Since “no rejection” does not mean “to be accepted”, we need to take more care with the possibility of being damage with this attribute. Therefore:

\[
\sum_{i=1}^{5} \Pr(H_d = S_i) = 1 \quad \text{where} \quad S_i \in \{N, U, C, Dr, De\}
\]

For final classification, the points will be marked by the attributes with maximum probability more than 0.5 (i.e. the attribute with absolute majority). If none of the attributes would attain absolute majority, that point has to be ignored or reinspect visually. If \( P_a \) : if \( \Pr(H_d = S_k) > 0.5 \) then “P_a is attributed as \( S_k \”).

5. AUTOMATIC INTERPRETATION OF DAMAGED BUILDINGS

For any desired and delineated region, the presented method is able to detect and classify damaged points. This region may be a polygon that identifies building rooftop. However, extracting details of damaged buildings would be possible if appropriate resolution in both imagery data and surface model is available (Schweier and Markus, 2004). We should set prior probabilities concerning rooftop area of a man-made object. Before an earthquake, a prior probability should be set to one and then only the second part of the BN will be active for detecting damages. After an earthquake, a prior probability for any specific building can be estimated if technical data about the building construction and/or severity level of earthquake are available. Otherwise, equal prior probabilities will be set. Damaged parts of each building are highlighted by “Demolished” and “Dropped” attributes. Moreover, some points may be marked by “Changed”
attribute when the BN classifier is doubtful about being damaged or undamaged. After pointwise assessment, with respect to the area of a building the ratio of damaged parts is estimated. Final classification is performed through “if-then” rules. Regarding the damaged parts of a rooftop, we define two levels of destruction for likely collapsed and certainly collapsed structures (DL1, DL2, e.g. 20% for likely collapsed and 50% for certainly collapsed). Those buildings that are certainly collapsed should be classified as “Partially” or “Totally” collapsed (EMS98: Grade 4,5). The certainly collapsed buildings are subject to more investigation to discover the details of demolition. Considering the proportion of “Demolished” and “Dropped” points, more details about collapsed buildings are extracted. In addition, we assume buildings with average height reduction less than one-meter per storey are recognized as “Partially collapsed” (still standing stories). The likely collapsed buildings have to be rechecked, this time including those points labelled by “Changed” attributes. The building is classified as “Partially collapsed” if (De + Dr + C) > DL2, otherwise it is classified as “Substantial damage” (EMS98: Grade 3). Also, we need to define a minimum level of “Undamaged” points for recognizing undamaged buildings (UL, e.g. 60%). Ultimately, the last if-then rule examines the structure for the final condition of an undamaged building or classifying it as “Moderate damage” (EMS98: Grade 2). The following instructions summarize how to interpret and classify a damaged building automatically:

- Calculate ratios of “De”, “Dr”, “C”, “U” attributes and average heights of the building before and after earthquake (hb, ha).
- Calculate: D = De+Dr and d = hb-ha and estimate number of building stories: s = hb ÷ 2.5 (one-storey building height = 2.5m)
- Define two levels for partially and totally collapsed buildings: DL1 = 20%, DL2 = 50% and one level for undamaged buildings: UL = 60%
- if (D + C > DL2) then {
  if (d > s) then
    Classified as: “Totally collapsed (G5)”
  else
    Classified as: “Partially collapsed (G4)”
} /* Looking for more details of collapsed building*/
- Affix: “-inclined, overturned or pancake collapsed”
- if (Dr > DL2) then
  if (Dr > DL1) then
    Affix: “-heap of debris with plates”
  else
    Affix: “-heap of debris”

6. Empirical investigations

6.1 Earthquake data set

To evaluate methods and verifying numerical results, a dataset was selected from aerial images of Kobe city before and after the earthquake. A set of aerial photographs, which were taken before (1991) and after (1995) the earthquake was prepared. It includes RGB colour stereo pairs of images before and a stereo triplet of images after the earthquake. The pre-event images were acquired by the aerial camera system Wild 15/4 with focal length 153.05mm. They were taken at a flight altitude 986m with an image scale of 1:6000. The post-event images were acquired by the aerial camera system RC-30 Leica with focal length 152.95mm and were taken at flight altitude 750m and 1:5000 image scale. The pre- and post-event photographs had been scanned at 30 and 20 micron, respectively (ca. 18 and 10cm of pixel size on object space). DSMs were created automatically from both pre- and post-earthquake aerial images using the SAT-PP software, which is efficient in-house developed software of IGP-ETHZ. The root mean square error value for checkpoints in pre- and post-earthquake DSMs are 2.37 and 2.13 meter, respectively.

6.2 Experimental results

The proposed methods including segmentation, features extraction and classification by means of Bayesian Network have been implemented and produced as stand-alone software. Using the networks discussed in the previous section, the performance of the system was analyzed. In particular the ability of the proposed system for damage assessment of buildings was tested. Figure 5 shows some sample buildings that first were segmented using the Bayesian reasoning network and then classified into damage categories using if-then rules (equal-appearing windows have different size). The attributes were recorded at equally spaced points (50 cm) within building polygons including: “Demolished”, “Dropped”, “Changed” and “Undamaged” represented by red, pink, yellow and green points respectively. Figures 5(a),(b) demonstrate some totally collapsed buildings from the Kobe dataset. The developed system will be able to extract more details about remaining rubble and debris type. Figure 5(b) shows a 2-storey building in Kobe that after the earthquake is completely collapsed. Automatic interpretation could give us a hint about huge debris with large plates. The secondary information about the type of debris facilitates rescue operations and recovery programs. The case of Figure 5(c) a building is estimated to be 5-story and classified as partially collapsed into “one-story pancake collapse” category. After an earthquake, buildings might be removed from their initial locations while still standing. Commonly, serious dislocations may cause to damage soft first storey and the resulting height reduction will be detectable.
Figure 5. Results of automatic damage interpretation for sample buildings of Kobe city - the left two columns: pair of aerial images before and after the earthquake, the right column: segmented buildings and their damage interpretation.

Figure 5(d) shows a dislocated building that moved to the next neighboring building while it is completely collapsed. When the dislocated house partly occupies adjacent footprint, it is quite likely to misclassify a totally collapsed as a partially collapsed building. Also, significant blunders of DSMs cause a similar mistake where low-rise collapsed buildings are located near to high-rise ones. In addition, DSMs generated by image matching software may contain substantial errors in low-textured area of the image. Nevertheless, the experimental results to detect totally collapsed structures are quite promising and the proposed system is still successful for many structural damages containing either heap of debris or inclined layers. Moderate structural damages (substantial damage) are represented as Grade 3 of EMS98. This category describes buildings with large and extensive cracks in walls, detached roof tiles, failure of rooftop elements and gable walls and surrounded by debris and rubbles. However, the proposed system concentrates on building footprint regardless of its surrounding. In proposed system, objects are divided into segments with related attributes and therefore small damaged
parts can be detected. Figure 5(e) shows a building that is not collapsed but some segments of the rooftop have been damaged which is classified as substantial damage (Grade 3). Figures 5(f) presents a burned building with slight structural damages. In this case, the classifier is able to explore dark parts of the building attributing scorched sections into “Changed” points. With relation to damage rate and selected thresholds, these buildings are classified as Grade 2 of EMS98 categories (Moderate damage). Figures 5(g) shows an undamaged building that is classified correctly.

Table 2 presents numerical comparison of automatic damage interpretation with visually damage classification. The criteria of damages interpretation using aerial stereoscopic images was described in Rezaeian and Gruen, 2011. For tri-level classification (“Uncollapsed”, “Partially collapsed” and “Totally collapsed”) out of 637 buildings in the Kobe dataset, 571 buildings are correctly classified resulting an overall accuracy 89.8%. In addition, a validation for multi-level EMS classes is performed with respect to our referenced data extracted visually. Omission and commission errors for (G1&G2) and (G5) were calculated 9.7%, 13.2% and 5.6%, 2.7% respectively. Considering visual interpretation criteria for G3, one needs to detect surrounding debris. It is foreseen that the EMS-G3 being undetectable with only roof analysis approach. Nevertheless, the reasoning system considerably succeeds to extract details of collapsed buildings. It should be noted that due to inherent ambiguity in definition of collapse categories, the results of interpretation that are performed manually by different human interpreters could be dissimilar. In Table 2, we assume shaded cells exhibit correct classification. Accordingly, the proposed system achieves 85.6% of overall accuracy for damage classification with details about collapsed buildings.

Table 2. Results of automatic interpretation of damages compared with visual interpretation – Kobe dataset (637 buildings).

<table>
<thead>
<tr>
<th>Bayesian Network Reasoning system</th>
<th>Uncollapsed</th>
<th>Partially collapsed (G4)</th>
<th>Totally collapsed (G5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>G1&amp;G2</td>
<td>G3</td>
<td>I</td>
</tr>
<tr>
<td>G1</td>
<td>198</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>G2</td>
<td>25</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>G3</td>
<td>9</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>G4</td>
<td>I, P, O</td>
<td>H with plates</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>H</td>
<td>3</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>No detail</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>G5</td>
<td>I, P, O</td>
<td>H with plates</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

7. DISCUSSION AND CONCLUSION

This paper showed an innovative approach for macro-seismic damage assessment in urban areas, using remote sensing techniques for high-resolution aerial imagery. In this contribution we focused on procedures, which start with gathering evidences from image segments and end up with inferring on every point in object space. Using line-based segmentation as an abstraction of building shape, it is possible to compare geometries of features, evidencing soft damages, reducing the effects of DSM errors. We presented a methodology for using Bayesian networks to a multi-view and multi-modal damaged object description. An augmented Bayesian network, which handles the combination of varying numbers of evidence sets has been introduced. Experimental results show that the suggested approach is promising. The more critical aspects of this work refer to the degree to which the low-level image feature extractors are reliable enough to provide evidence for infences about damaged buildings and to the issue of how well Bayesian inference, per se, is an adequate model for how experts combine such diverse information in the process of image understanding. The presented results support both aspects of the model with respect to recognition performance, although more extensive testing is clearly required. It is anticipated that this general theoretical approach has potential to yield automatic urban damage estimation.

Traditionally, the approaches of classifications can be divided into two main categories: pixel-based and object-based analyses. Both of these approaches assign attributes to “image pixels” either one-by-one or segment-by-segment. In the proposed system attributes are assigned to “object points” based on features extracted from segments of multi-image data. In other words, the system starts with gathering evidences from multi-image segments and end up with inferring on every point in object space. This approach may be converted to a traditional object-based classifier employing single images because all pixels inside each segment of image are only classified based on the evidences extracted from that segment of image.

However, the experimental results of this study have been negatively influenced by a number of factors, which in the future can be avoided by the following measures:

- Use of digital images – compared with the film-based aerial photography, digital cameras have more dynamic range and optical sensitivity and the images are ready for computation after data acquisition. This improves the image information with better radiometric depth, which allows to look into the shadows and also opens the possibility of faster (on-line) processing.
- Use larger focal length (“normal angle” images) or Linear Array camera images – helps against occlusions. Oblique
images provide valuable information about the facades of the buildings. This makes it possible to see damages on the walls.

• Fly with larger image scale – this improves the interpretability of images (higher level of detail).

8. REFERENCES


