CLASSIFICATION OF BUILDING DAMAGES BASED ON LASER SCANNING DATA

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ABSTRACT:

Due to the possibility of acquiring precise height data of large areas rapidly, airborne laser scanning systems are particularly suitable for obtaining information about the damage situation immediately after a disaster in large scale. This paper presents a technique for the detection and classification of damages occurring on buildings in affected areas. It is based on the comparison of pre-event building models composed of planar surfaces with planar surfaces extracted from laser scanning data acquired directly after the disaster. In a first step, segments are created by superposing the pre- and post-event surfaces. Subsequently, for every segment the geometrical characteristics of the corresponding pre- and post-event surface are compared. Finally, the segments are assigned to damage types using a fuzzy logic classification approach. The results achieved for each processing step by applying the method on data containing real building damages are presented and analysed.

1. INTRODUCTION

Disasters like earthquakes cause many casualties every year. In many cases people are trapped in collapsed buildings and have to be rescued. Mostly, time plays a very critical role in this process. Furthermore, resources are short and have to be employed efficiently to save as many lives as possible. This shows the necessity of a fast and extensive damage analysis. Therefore, one project of the German Collaborative Research Centre (CRC) 461 "Strong Earthquakes: A Challenge for Geosciences and Civil Engineering" deals with the development of methods for the automatic detection and classification of building damages. Since the resources required for rescue activities depend among others on the damage types of the affected buildings (Schweier and Markus, 2004), it is not only important to find out whether a building is damaged or not but also to receive information about how it is collapsed.

The damage analysis described in this paper is based on the comparison of planar surfaces composing pre-event building models and planar surfaces derived from post-event airborne laser scanning data. Airborne LIDAR data are used because laser scanning allows a rapid and extensive acquisition of height data without the necessity of entering destroyed areas. The use of laser scanning data for the detection of building damages after disasters has already been proposed in several publications, e.g. (Murakami et al., 1998), (Vögtle and Steinle, 2004), (Vu et al., 2004). Most of these approaches have originally been developed for the detection of changes in urban areas. Until now, they have never been tested on data containing real building damages.

The results of this damage interpretation represent one main input of the Disaster Management Tool (DMT) also developed within the CRC 461 (Markus et al., 2006). The aim of the DMT is the support of decision makers, surveillance and intervention teams during disaster response.

In this paper a building damage detection and classification technique is presented. It is based on a segmental fuzzy logic approach. However, only the situation of the buildings contained in the pre-event data set can be regarded. The results achieved by applying this method on data containing buildings with different damage types are demonstrated and interpreted.

2. DAMAGE TYPES

During a classification process unknown patterns are assigned to a priori given classes. Therefore, the classes which shall be discriminated have to be defined before the classification. Due to this, a damage catalogue was developed containing the different damage types of entire buildings after earthquakes (Figure 1) (Schweier and Markus, 2004; Schweier and Markus, 2006). Moreover, the damage catalogue includes for every damage type a description and some geometrical features like *volume* and *height reduction*, the *change of the inclination of building surfaces* as well as the *surface structure* and the *size of the recognisable planes*. For these features qualitative or quantitative values were determined by analysing pictures of more than 100 damaged buildings. Quantitative information is defined by numeric values, e.g. a *heap of debris* has a *volume reduction* of 60-80%. To express qualitative information linguistic terms are used, e.g. the *volume reduction* of a *multi layer collapse* is *small*. For the development of the damage catalogue the special characteristics of aerial data acquisition

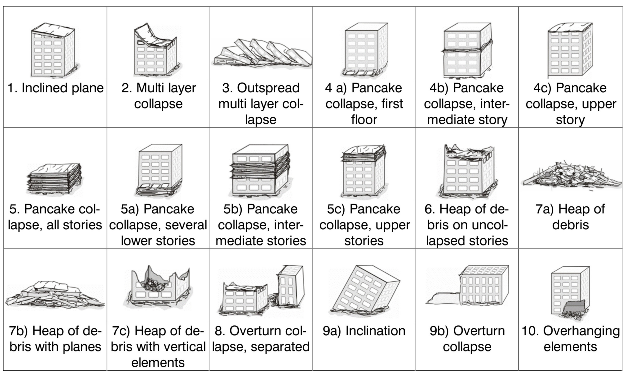

Figure 1: Compilation of damage types (Schweier and Markus, 2004)

were taken into account. This means that attention was paid to the fact that the geometrical features characterising the single damage types can be derived from aerial data (e.g. laser scanning).

As in the presented approach only changes inside the pre-event building outlines are examined (see section 1), features like *debris structure outside the footprint* cannot be used for the discrimination of the various damage types. This implicates that damages characterised very well by these features (e.g. *overturn collapse*) may not yet be identified within the current classification procedure which should be extended in future.

Concerning damage types 4a), 4b), 4c) and 5, 5a), 5b), 5c), respectively, it seems to be impossible to find out which storey has collapsed by using aerial data only. Hence, these damage types were summarised as follows:

- Pancake collapse of one storey
- Pancake collapse of more than one storey

The difference of a *pancake collapse of one storey* and a *pancake collapse of more than one storey* is characterised by the quantity of the *volume* and *height reduction*. Obviously, damage type 5 has a higher *volume* and *height reduction* than damage type 4. But since the number of collapsed storeys can only be determined reliably if the height of a floor is known, this discrimination is very fuzzy if it is unknown.

Furthermore, the different types of debris heaps (7a), 7b), 7c)) are also very difficult to distinguish. As a consequence, they are merged as well. Damage type number 10 (*overhanging elements*) cannot be recognised if only aerial data (e.g. LIDAR) are used. As a result, the following damage types are distinguished in the classification process:

0. Unchanged
1. Inclined plane
2. Multi layer collapse
3. Outspread multi layer collapse
4. Pancake collapse of one storey
5. Pancake collapse of more than one storey
6. Heap of debris on uncollapsed storeys
7. Heap of debris
8. Overturn collapse, separated

9a. Inclination

3. DATA

The test site of this study is an area of the *Swiss Military Disaster Relief* used for practising search and rescue activities (Figure 2). It is located close to Geneva and has a size of about 500 m × 800 m. The specialty of this area is that undamaged buildings as well as damaged buildings with different damage types are located on it. Table 1 summarises the damage types occurring on the buildings marked in Figure 2.

Building no.	1	2		3	4	5	6a	6b	7
Damage type	5	5 + 9a		1	0	5	0	5	7
Building no.	8	9	10	11	12	13	14	15	16
Damage type	7	3	7	7	0	0	0	0	0

Table 1: Damage types of the buildings marked in Figure 2

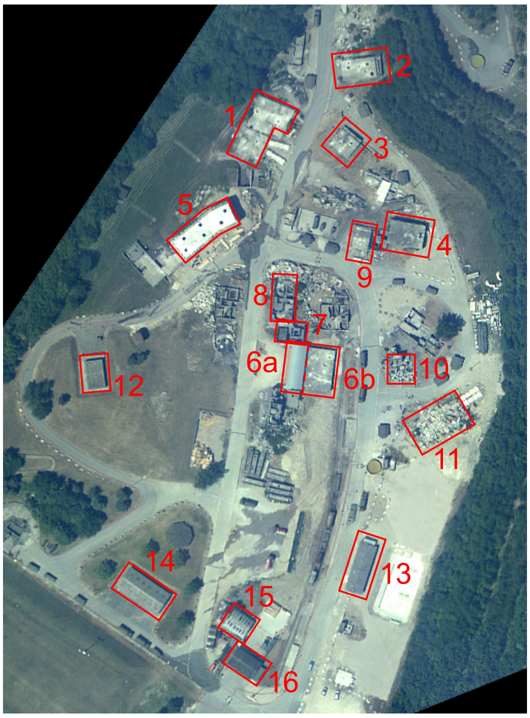

Figure 2: Aerial image of the test site

In 2004 a laser scanning flight was carried out in order to acquire height data of this test area. Therefore, a TopoSys Falcon II sensor was used. The original point clouds were transformed into DSMs (1 m raster width) having an accuracy of ± 0.5 m in position and ± 0.15 m in height. The described approach is based on raster data because of the better performance concerning memory access and the well defined neighbourhood. But it has to be mentioned that in principle the method can also be adapted to point clouds.

Normally it is a problem to get LIDAR data of areas containing damaged buildings. In this study it is exactly the other way round. This means that no real laser scanning data of the pre-event state are available. On this account CAD models of the undamaged buildings were reconstructed by means of construction plans and photographs.

4. CLASSIFICATION OF BUILDING DAMAGES

In this section the whole workflow of the approach for classifying building damages is described. First of all a normalised DSM (nDSM) is needed for the post-event date. An nDSM contains only the 3D objects on the Earth's surface like buildings and vegetation. It can be derived from the DSM by subtracting a digital terrain model (DTM) (Oude Elberink and Maas, 2000; Steinle and Vögtle, 2001). For the generation of DTMs from laser data many methods have been proposed (e.g. Weidner and Förstner, 1995; Axelsson, 2000; Vosselman, 2000; Tóvári and Pfeifer, 2005). In this study the approach of (von Hansen and Vögtle, 1999) is applied which uses a convex-concave hull (TIN densification).

Figure 3 displays the pre-event data of the test site. In Figure 4 the post-event nDSM derived from last echo data is visualised. It has to be indicated that terrain and vegetation have not been modelled in the pre-event data based on CAD models.

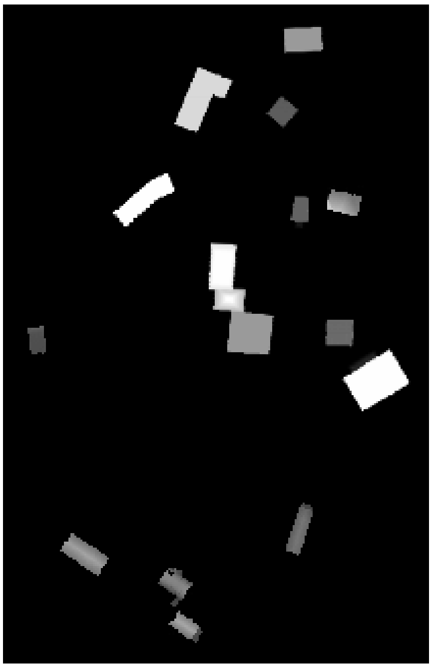

Figure 3: Pre-event data generated from CAD models

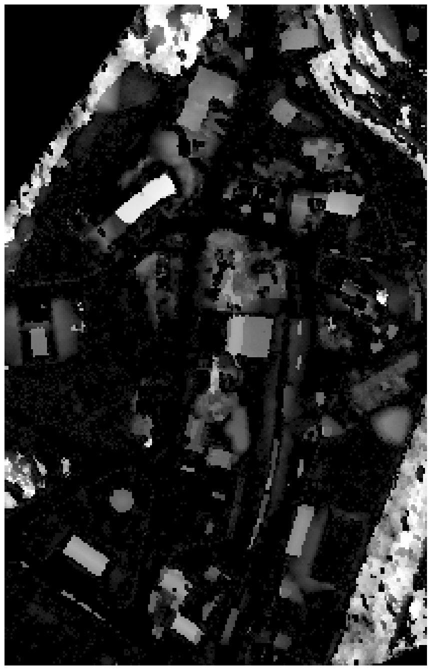

Figure 4: Last echo post-event nDSM

4.1 Generation of pre-event building models

As already mentioned in section 1, pre-event building models are needed as basis for the classification. These models can be created by using different methods such as photogrammetry, terrestrial measurements or construction plans (Figure 5(a)). Airborne laser scanning itself is a suitable technique for the extraction of building models (Brenner and Haala, 2000; Vosselman and Dijkman, 2001; Rottensteiner et al., 2005; Schwalbe et al., 2005). For this purpose, (Steinle, 2005) proposed a method which starts with the extraction of planar surfaces from a laser scanning derived nDSM (see section 4.2). Afterwards, the neighbourhood relations (topology) of these surfaces are analysed and adjacent planes are intersected. This results in building edges which can be intersected again in order to determine the corners of the building (CAD model).

Since only changes within buildings included in the pre-event data are inspected during the classification step, the building outlines have to be extracted from these building models before the further analysis can start.

4.2 Creation of segments for the classification

Two main features that characterise the different damage types are the *size of the recognisable planes* and the *change of inclination of the building surfaces* (see section 2). For this reason, planar surfaces are extracted from the post-event nDSM (see Figure 5(b)) by applying a region growing algorithm starting from a seed region which fulfils the condition that the assigned points are approximately lying in a plane (Steinle, 2005; Rehor and Bähr, 2006). For testing the affiliation of a neighbouring pixel to the currently considered plane, a global test and a test for blunders in a Gauss-Markov model are used as homogeneity criterion. For every detected segment the plane of best fit is estimated by least squares adjustment. Due to taking into account only planar surfaces lying inside building contours (section 4.1) during the further processing steps, the segmentation algorithm is only applied on points lying inside a building outline plus a buffer of 3 m.

After planar surfaces have been extracted from the post-event laser data, new segments are created by superposition of the pre- and post-event planar surfaces (Figure 5(c)). This means that each of these new segments corresponds to one of the pre- and one of the post-event surfaces. As a consequence, for these segments features like the *change of inclination* or the *volume* and *height reduction* can be calculated (see section 4.3).

During the segmentation of planar surfaces not all pixels are assigned to segments. Some pixels remain unsegmented. For these pixels no plane of best fit can be estimated. In consequence, the *change of inclination* cannot be determined. So these pixels are excluded from the building damage classification and treated in a special way. For each pixel staying unsegmented the difference of its pre- and its post-event elevation is calculated. This height difference h_{diff} is analysed and classified as follows:

$$\begin{aligned} |h_{diff}| &< t_1 : \text{ unchanged} \\ h_{diff} &> t_1 : \text{ reduction} \\ h_{diff} &< -t_1 : \text{ increase} \end{aligned}$$

Due to the fact that damage types like *heaps of debris*, *outspread multi layer collapses* or *overturn collapses* have a very irregular *structure of surface*, the assumption can be made that many unsegmented pixels occur in areas affected by these damage types.

4.3 Feature extraction

In order to assign the segments to a priori determined classes (see section 2), features have to be defined and extracted for each segment (see section 4.2). These features should be chosen in such a way that they cause a high discrimination between the different classes. With respect to the damage catalogue the following parameters were determined for every segment:

- Volume reduction
- Height reduction
- Change of inclination
- Size

The volume reduction expresses the ratio of the difference between pre- and post-event volume of the segment and the pre-event volume. The height reduction is defined as the ratio of the difference between the maximum pre-event and the maximum post-event height of the segment to the maximum pre-event height. The change of inclination is defined as the angle between the normal vectors of the corresponding pre- and post-event planes. Due to the usage of raster data, the segment size can be calculated easily by multiplying the number of pixels associated with the segment by the pixel size.

4.4 Fuzzy logic classification of building damages

For the classification of building damages a *fuzzy logic* based technique has been developed. The theory of fuzzy sets was introduced by (Zadeh, 1965) in order to model uncertainties. While in ordinary Boolean logic an element either belongs to a class or not, fuzzy logic enables to define a grade of membership (Tilli, 1993).

A fuzzy logic classification always starts with the definition of membership functions for every class and every feature (*fuzzification*). To simplify matters in this study, they are composed of line segments although in general they do not have to be linear. Furthermore, the a priori knowledge about the damage types defined in the damage catalogue is taken into account during this step (see section 2). This means that the qualitative and quantitative descriptions of the features are converted into membership functions for every damage type. By means of membership functions a degree of membership $\mu_{i,j}$ can be calculated for every segment with every parameter j (here j=4 (section 4.3)) according to every class i (here i=10 (section 2)).

The combination of the single membership values $\mu_{i,j}$ for the j different features results in the degree of match μ_i for every class i (*inference process*). It can be realised by different operators (e.g. minimum and maximum operator (Zadeh, 1965), algebraic product (Tilli, 1993), etc.). (Weidner and Lemp, 2005) propose the employment of the mean or the median of the single values. Among a lot of other possibilities these five operators have been tested in this study.

Finally, a decision for one class is made by applying the maximum operator, i.e. the currently considered segment is assigned to the class i with the highest value μ_i.

5. RESULTS

In the following the results obtained by applying the whole approach on the data of the test site are presented. Figure 5(a) shows the planar surfaces of the pre-event buildings (section 4.1). The post-event planar surfaces are visualised in Figure 5(b). The segments resulting from the superposition of the pre- and post-event surfaces are displayed in Figure 5(c). The classification is based on these segments.

The comparison of the five different operators for the inference process shows that the best results are achieved by the algebraic product, while the other operators prove to be less suitable. Therefore, the results obtained by the product operator are visualised in Figure 5(d). This verifies the achievements of (Tóvári and Vögtle, 2004). During their investigations concerning the classification of 3D objects in laser scanning data the product operator also provided the results with the highest classification rate.

A closer look at Figure 5(d) in combination with Table 1 shows that main parts of the buildings 1, 3, 4, 6a, 6b, 7, 8, 10, 11, 12, 13, 14 and 16 are classified correctly. For building 5 a *pancake collapse of one storey* was determined instead of a *pancake collapse of more than one storey*. As mentioned in section 2 the discrimination between these two damage types is very difficult if the height of a floor is not known. But if the two types of pancake collapse would be fused, a correct decision would be gained.

A similar case occurs at building 2 (Figure 5(e)). Its real damage type is a combination of a *pancake collapse of more than one storey* and an *inclination*. The classification proposes damage type number 4. Due to the fact that each segment can be assigned to only one damage type the general solution *pancake collapse* would be acceptable. Furthermore, it has to be mentioned that the class with the second highest degree of match for the main segment of building 2 is *inclination*. As a consequence, further research should examine if an improvement can be achieved by taking not only the class with the highest degree of match into account but also the one with the second highest value. This means that for example specific combinations of damage types could be allowed.

Figure 5(d) in connection with Table 1 and Figure 2 confirms the assumption that many unsegmented pixels showing a height reduction occur in case of debris heaps (section 4.2). If this is taken into account the determined damages of the buildings 7, 8, 10 and 11 can be considered as correct.

Building 9 is one of the misclassified buildings (Figure 5(f)). In reality it is affected by an *outspread multi layer collapse* but it is classified as an *inclination*. This can be explained by the fact that an *outspread multi layer collapse* is characterised by the extension of debris outside the former building contour line which is not yet regarded in this status of the approach. Therefore, it is not surprising that the classification is not correct.

Building 15 is an exception because it has a barrel-shaped roof (Figure 5(g)). Hence, this roof type is not composed by planar surfaces in the CAD model (section 2). Since the whole approach is based on the comparison of planar surfaces, the region growing algorithm described above (section 4.2) is applied on the pre-event data of this building. But although building 15 is unchanged (Table 1), the surfaces extracted from the pre- and post-event data are not the same. Thus, the inclination change of the corresponding pre- and post-event planes is significantly larger than zero and the segments are classified as *inclined planes* instead as *unchanged*. As the only difference between the damage types 0 and 1 is the change of the orientation that is a bit larger for damage type 1, it is obvious that building 15 is the only misclassified building without any damage. In addition, more pixels remain unsegmented during the segmentation of planar surfaces than in case of buildings with gable or flat roofs.

6. CONCLUSION

A new approach for the classification of building damages after disasters like earthquakes was presented. It is based on the comparison of building models derived from pre- and post-event data. It starts with a segmentation of planar surfaces, followed by the generation of segments on which the fuzzy logic classification can be applied. Finally, these segments are

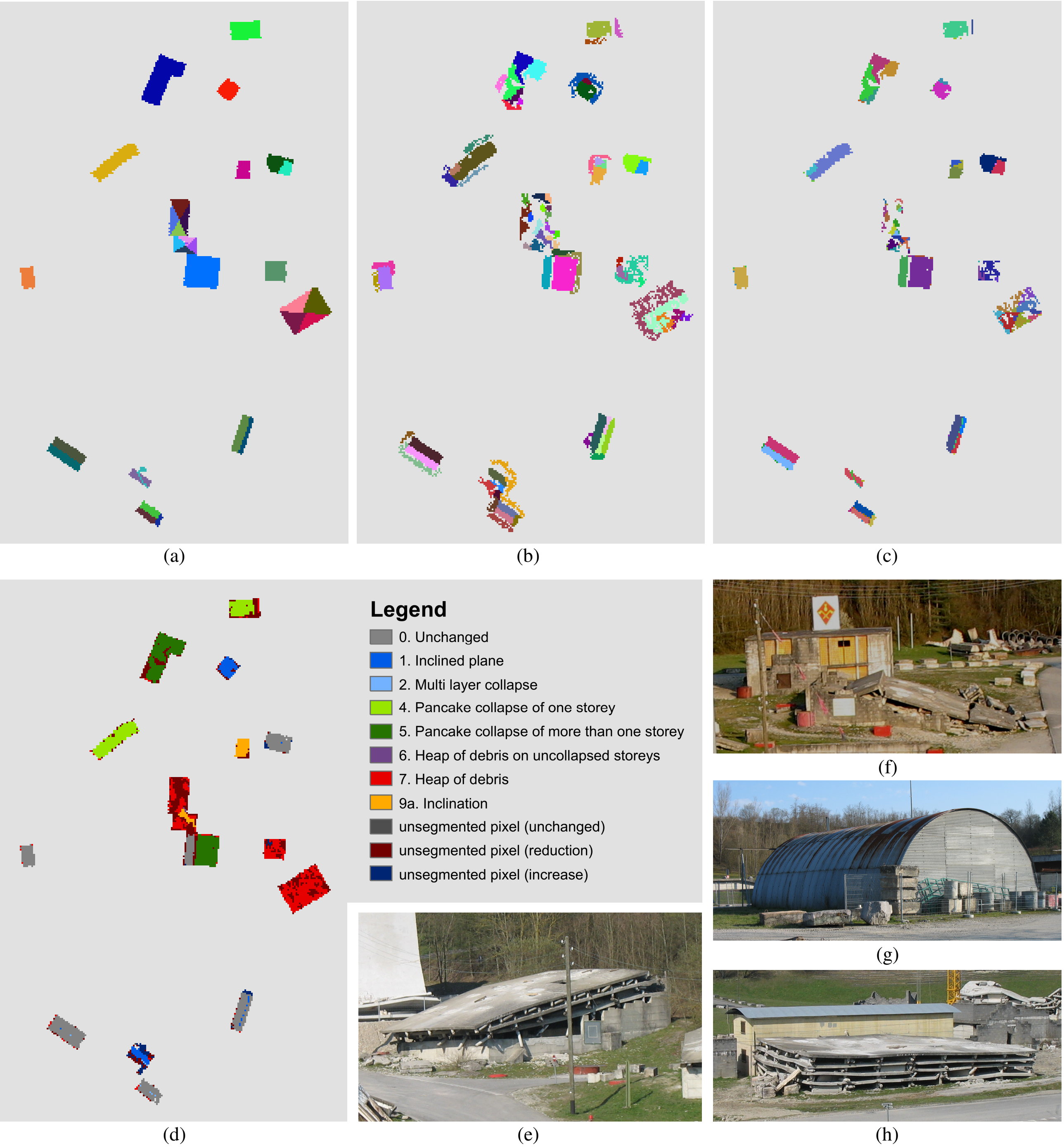

Figure 5: a) Planar surfaces of the pre-event buildings. b) Planar surfaces extracted from the post-event data. c) Segments used for the classification; they are created by a superposition of the pre- and post-event planar surfaces. a) - c) Each segment is displayed in another random colour. d) Classification results achieved by using the product operator for the inference process. e) Photograph of building 2. f) Photograph of buildings 4 and 9. g) Photograph of building 15. h) Photograph of building 6.

assigned to damage types according to there height and volume reduction, their size, and there change of inclination.

The results achieved for data of a test area containing real building damages are very promising although only changes inside the pre-event building contour are analysed so far. Thus, in future further investigations should be carried out to extend the approach in order to include the situation outside the former building areas into the analysis.

During the classification process each of the segments is classified on its own. As a result, different segments belonging to one building may be assigned to different damage classes. On the one hand, this is advantageous because one building can be affected by more than one damage type (e.g. building 6 (Figure 5(h)). On the other hand, the possibility exists that most of the segments belonging to one building are classified correctly as the same damage type but some small segments are misclassified (e.g. building 13). As a consequence, it should be investigated in further research if an improvement can be achieved by considering the damage types of adjacent segments. Besides, the results might be optimised if the class with the second highest degree of match is also taken into account.

Another aspect requiring further research is the treatment of pixels not assigned to a planar surface in one of the two states. It was pointed out that they concentrate in areas affected by specific damage types. Hence, they should also be classified based on triangulated surface description instead of planes.

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