IMPROVEMENT OF BUILDING DAMAGE DETECTION AND CLASSIFICATION BASED ON LASER SCANNING DATA BY INTEGRATING SPECTRAL INFORMATION

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ABSTRACT:

This paper presents improvements of an existing building damage detection and classification method based on airborne laser scanning data especially identifying damage types in affected areas. Furthermore, it deals with the question if the integration of spectral information like laser intensity data, multi-spectral scanner data or high resolution digital orthophotos can contribute to a further enhancement of the classification results. For this purpose, the characteristics of these three different data types for undamaged and damaged buildings are analysed and different texture parameters are tested in order to select features which can be included into the classification process. The results obtained for different input data and textures are compared and analysed.

1. INTRODUCTION

Every year disasters cause high human and economic losses. After a disaster, the situation is often chaotic and available resources are not used efficiently. In order to support search and rescue activities in saving as many trapped persons as possible, a fast and extensive damage analysis is required. Such a damage analysis should – amongst others – detect and classify damage types occurring on buildings caused by a disaster. For data acquisition, airborne laser scanning (ALS) is particularly suitable since it allows capturing 3D data of large areas in a short time without the need of entering affected zones.

In order to support search and rescue activities in an optimal way, different requirements have to be fulfilled by a damage detection method. It has proved to be not enough to distinguish only between undamaged and damaged buildings as presented in many approaches (e.g. Rezaeian and Grün, 2007; Vu et al., 2007; Sumer and Turker, 2006). In fact, damaged buildings should be further analysed and their damage types should be classified in more detail because they require different rescue strategies in the context of an optimal disaster management.

For that purpose, a building damage detection and classification method was already developed by (Rehor, 2007). In this paper new improvements on that method contributing to enhanced classification results are presented. Furthermore, it is investigated if the integration of spectral information can further improve the results. Therefore, the characteristics of laser intensity data as well as multi-spectral data for undestroyed and destroyed buildings are analysed and described. Moreover, different texture parameters are investigated in order to include these data into the classification.

2. RELATED WORK

The number of publications concerning building damage assessment after disasters increases consistently. Many approaches use spectral data (aerial images or high resolution satellite images) for damage detection. In this context, different possibilities exist. Either, the changes of spectral and textural characteristics between pre- and post-event images are analysed (e.g. Rezaeian and Grün, 2007; Chesnel et al., 2007) or only post-event images are utilised (e.g. Vu et al., 2007; Sumer and Turker, 2006). In the first case, it is assumed that spectral and textural characteristics change when a building collapses. In the second case, different characteristics of undamaged and damaged buildings only in post-event data are applied. In both cases, especially edge information is used for detecting and discriminating collapsed and un-collapsed buildings.

(Rezaeian and Grün, 2007) combine geometric and textural features in order to distinguish between collapsed, partially collapsed and undamaged buildings. Besides the volume reduction derived from the difference of pre- and post-event digital surface models generated from stereo aerial images a criterion for edge existence is used. For this purpose, the Canny operator is applied to the post-event images. Afterwards, the detected edges are compared to vector lines extracted from the pre-event images. The rate of fit between both is an indicator for the degree of damage of the building.

(Chesnel et al., 2007) assign buildings to four different classes according to the European Macroseismic Scale (EMS). For this purpose, they use a correlation coefficient in order to determine information about the amount of similarity between pre- and post-event images.

(Vu et al., 2007) use a two-stage approach. Firstly, debris areas are identified by applying the Prewitt operator for detecting edges. Secondly, the retained buildings are identified with an object-based image analysis method using multi-spectral information and spatial relationships. Afterwards, the overlap of the retained buildings and the debris areas is analysed in order to determine the damage degree of the buildings.

In the approach of (Sumer and Turker, 2006), collapsed and un-collapsed buildings are discriminated using a combination of a building grey value and a gradient orientation approach. It is assumed that collapsed buildings show higher brightness values than un-collapsed ones and that their gradient directions are randomly distributed whereas the orientation of the gradients for un-collapsed buildings is more regular.

3. DAMAGE CLASSIFICATION METHOD OF IPF

The original building damage detection and classification method developed at IPF was presented in detail in (Rehor, 2007) and (Rehor and Bähr, 2007). Therefore, only a short summary will be given at this point.

In order to detect and classify changes in building geometry, the comparison of post-event data and pre-event building models is necessary. The original method starts with the extraction of planar surfaces from post-event ALS data. These planar surfaces and their corresponding roof planes of the reference buildings are superposed and in this way new segments are created on which the classification can be based on. Therefore, the features *volume* and *height reduction*, *change of inclination*, and *size* are determined for each of the generated segments. In the next step, the values of these features are introduced into a fuzzy logic classification which assigns each segment to the damage type with the highest degree of match. In this approach ten different damage types are distinguished: *unchanged*, *inclined plane*, *multi layer collapse*, *outspread multi layer collapse*, *pancake collapse of one storey*, *pancake collapse of more than one storey*, *heap of debris on uncollapsed storeys*, *heap of debris*, *overturn collapse (separated)*, and *inclination*.

During the extraction of planar surfaces not every pixel can be assigned to one of these planes. Some pixels do not fit in any of the planes and remain unsegmented. In the last state of our approach (Rehor, 2007) those pixels are analysed totally on their own. For each, the difference between its pre- and post-event height is calculated and used for classification. During this process, the relations to neighbouring unsegmented pixels are not taken into account.

As a consequence, for unsegmented pixels it is only analysed if their height increased, decreased or stayed unchanged, but they are not assigned to different damage types. Although investigations showed that such unsegmented pixels with a significant height reduction accumulate in areas with damage types like *heap of debris*, neither this information is taken into account nor a distinction of different debris heaps – for example with and without vertical elements – is possible until now.

For the development of this classification technique normalised digital surface models with 1 m grid size have been used. They were derived from ALS data of the test site 'Epeisses' – a training area of the *Swiss Military Disaster Relief* located close to Geneva. This area contains several undamaged and damaged buildings. The damaged buildings show different damage types.

4. IMPROVEMENT OF DAMAGE CLASSIFICATION USING LASER SCANNING DATA EXCLUSIVELY

Several further developments of the original classification method were carried out in order to improve the achieved results. Firstly, a new feature was introduced for the discrimination of heaps of debris with and without vertical elements. This new feature is the standard deviation of the segment's median filtered height texture values determined with the Laplace filter (3×3 pixel). If the damage type *heap of debris* is the one with the highest degree of match, this standard deviation is used to decide whether or not there are vertical elements within this heap of debris because the value is significantly higher for *heaps of debris with vertical elements* than for *heaps of debris without vertical elements*.

Secondly, the analysis of pixels which do not fit to any planar surface larger than a given minimum size was improved. For this purpose, adjacent unsegmented pixels are clustered by a region growing algorithm. These clusters are also classified using a fuzzy logic approach. In this case, only the following damage types are discriminated at the moment:

- Unchanged
- Heap of debris
- Heap of debris with vertical elements

For the classification the features *volume reduction*, *minimum height difference*, and *contrast* are determined for each of these clusters. The volume reduction is calculated by adding up the volume reductions of the single pixel cells associated with the respective cluster. It is very small for unchanged buildings and very large for both types of debris heaps. For determining the minimum height difference, the difference between its pre- and post-event height is calculated for each pixel. The smallest of these values represents the minimum height difference. It also takes small values for unchanged buildings and great values for heaps of debris. For *heaps of debris with vertical elements* the minimum height difference is smaller than for *heaps of debris without vertical elements*. The determination of contrast is based on the so called grey level co-occurrence matrix. This matrix is determined for each segment and used to derive the parameter 'contrast' (Haralick et al., 1973) which is a measure for the local variations present in a cluster. Therefore, it is much higher for *heaps of debris with vertical elements* than for *heaps of debris without vertical elements.*

A third improvement is carried out after creation of segments and clusters, but still before classification. For this purpose, the average segment size is calculated for each building by dividing the total area of the building by the number of segments and clusters lying inside the contour of this reference building. If the size of a segment is smaller than 20 % of the average segment size, it is merged with the largest neighbouring segment or cluster. Thus, small segments are avoided occurring especially at borders of buildings with mainly large planes or due to chimneys or dormers. Such segments were often misclassified. However, small segments or clusters in areas with irregular surface structure are retained because in these areas the average segment size is small. Thus, the problem of misclassification of small segments among otherwise correctly classified segments (cf. Rehor, 2007) is at least partially solved.

5. IMPROVEMENT OF DAMAGE CLASSIFICATION BY INTEGRATING SPECTRAL INFORMATION

5.1 Spectral data

In addition to the commonly used geometric laser scanning data spectral information should be included in order to improve the classification of building damage types, especially for *heaps of debris* which have shown certain problems in the original method (cf. section 3). Two features seem to be useful: the change of spectral values and the change of texture. Due to the higher robustness of texture in comparison to spectral values, the extraction of texture parameters is preferred at first.

For the investigations in this study, three different types of spectral information are available:

- Laser intensity values
- Multi-spectral scanner data (RGB/CIR)
- Multi-spectral aerial images (orthophotos, RGB/CIR)

In the context of the Collaborative Research Centre (CRC) 461 'Strong Earthquakes: A Challenge for Geosciences and Civil Engineering' two laser scanning flights over the test site 'Epeisses' were carried out by TopoSys© (Germany) – the first in June 2004, the second in November 2004. In each case the laser intensities (0.5 m pixel size on ground) and the multi-spectral scanner data (0.5 m pixel size on ground) were acquired simultaneously. Additionally, digital orthophotos (RGB and CIR) were ordered from the Système d'Information du Territoire Genevois (SITG), Switzerland (0.16 m pixel size on ground) which had been captured in August 2005.

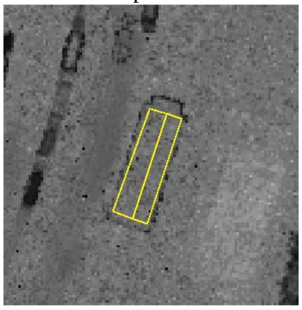
5.2 Texture parameters

In the literature a lot of different texture parameters can be found (e.g. Haralick, 1979). For application in this study, those parameters had to be selected which are suitable to distinguish between the different damage types of buildings. Therefore, different texture parameters have been tested: the classical Haralick parameters, Laplace operator, local curvature and standard deviation as well as Laws operators of HALCON© software package. Concerning Haralick parameters, best results could be obtained by 'homogeneity'. However, compared to other texture parameters like Laplace or Laws the results were significantly worse and Haralick parameters were not taken into account for further analysis in this study. Concerning Laws operator, all types have been studied. Besides filter type ES and EL best discrimination of building damage could be obtained by filter type SL. Details will be described in the following subsections. Due to the robustness concerning outliers (e.g. caused by chimneys, antennas, etc.), the median was used to determine texture values for each roof plane.

5.3 Analysis of laser intensity values

The laser intensity values were acquired by the ALS system of TopoSys© (Germany) with a wavelength of 1540 nm. As a laser scanner is an active system, it is almost independent of exterior lighting conditions. This is a great advantage in the field of disaster management with short reaction time as it makes data capturing possible also at night.

If buildings or other objects without changes in geometry or structure are compared in the data sets of the two flights (June/November 2004), it should be expected that only minor deviations of the spectral values occur caused by the influences of lighting conditions, daytime or other effects. Especially the texture values should be reasonably stable. However, the analysis showed that there are mostly large differences between the intensity values of the two acquisition dates (Figure 1). Unfortunately, these differences are not reasonably constant. There are buildings with large changes and others with intensity values remaining almost the same. Figure 2 shows the intensity images of an undestroyed and a destroyed building. The textures of these two buildings are very similar. The analysis of the extracted texture values for all buildings of the test site shows that even they vary in a large domain, i.e. the values for undestroyed and destroyed buildings overlap to a high percentage (Table 1). Therefore, the laser intensity values seem not to be suitable for this application and cannot improve the classification process of building damage.



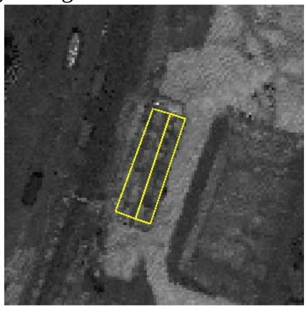
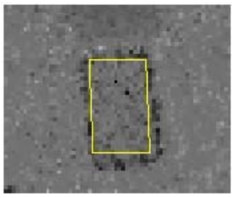


Figure 1. Intensity images of an unchanged building for two different dates, left: June 2004, right: November 2004



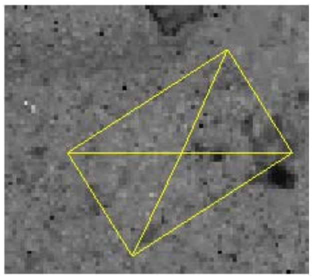


Figure 2. Intensity images of an undestroyed building (left) and a destroyed building (right)

Texture parameter	***Texture values***	
	Undestroyed buildings	***Destroyed buildings***
Laplace operator	25 - 80	35 - 100
Laws SL operator	20 - 95	25 - 135
Local curvature	25 - 55	35 - 70
Standard deviation	15 - 25	15 - 35

Table 1. Texture values (based on laser intensities) of undestroyed and destroyed buildings

5.4 Analysis of multi-spectral scanner data

The multi-spectral scanner data were acquired in four spectral bands (R, G, B, NIR) by an additional multi-spectral scanner operating simultaneously to the laser scanner inside the TopoSys© ALS system. Because it is a passive sensor, the spectral values are highly affected by the time of day, lighting effects like shadowing or haze. Therefore, larger changes of the spectral values may not only be caused by building damage but also by one or more of these influences. Consequently, pure spectral values cannot be used in this context while textures proved to be more robust with respect to these effects.

In Table 2 the texture values of the four spectral bands are given for one representative parameter (Laplace). It shows that a better separability between undestroyed and destroyed buildings can be observed for red and green than for blue and near infrared. Therefore, within this paper, only the results for red are commented in the following.

In order to analyse the suitability of the pre-selected texture parameters (cf. section 5.2) for classifying building damage, the obtained texture values are listed in Table 3. It has to be taken into account that only the changes of those values for the particular parameters in relation to their variability are relevant.

The absolute values cannot be compared between the different parameters.

Figure 3 shows the RGB scanner images of an undestroyed (a) and a destroyed (b) building as well as the results achieved by applying the Laplace operator (d, e), the Laws SL operator (g, h), and the standard deviation (j, k).

To assess the change of texture caused by a building damage the variability of the utilised texture parameter has to be taken into account. For this purpose, the values of the two flights were

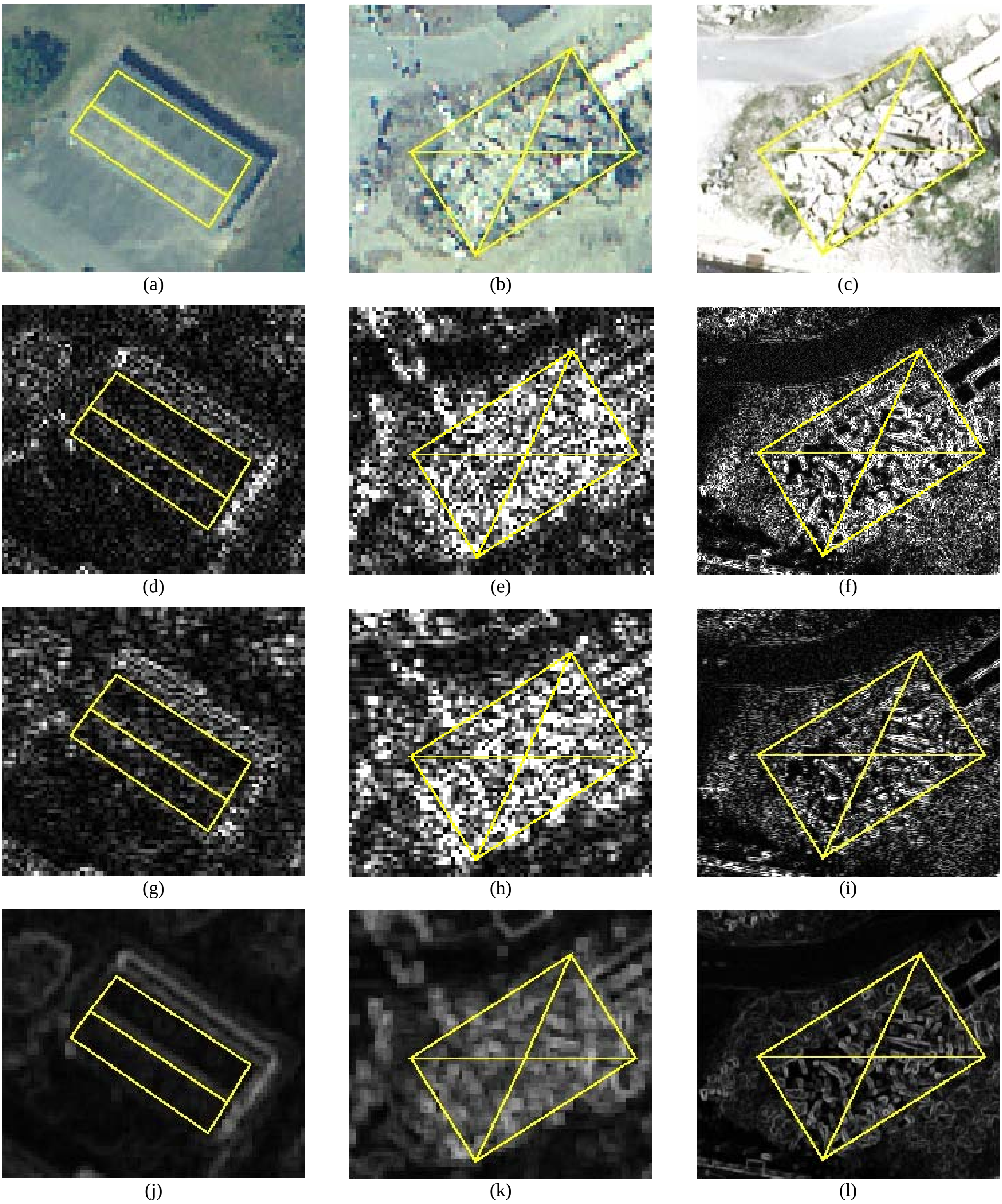


Figure 3. (a): Scanner image (RGB) of an undestroyed building, (b): scanner image (RGB) of a destroyed building, (c): orthophoto (RGB) of the same destroyed building, (d) - (f): texture images obtained by applying the Laplace operator on images (a) - (c), (g) - (i): texture images obtained by applying the Laws SL operator on images (a) - (c), (j) - (l): texture images obtained by applying the standard deviation on images (a) - (c)

compared for each building. The change values for undestroyed and destroyed buildings are specified in Table 4. Due to the lack of buildings destroyed between the two dates of data acquisition (the buildings of the test site had been destroyed earlier), the roof textures for the undestroyed status had to be simulated. Therefore, construction plans and information about roof materials were used to create adequate textures or typical ones were copied from other undestroyed buildings. It can be concluded that each of the examined parameters can be applied for an improvement of damage classification.

Texture parameter	***Texture values***	
	Undestroyed buildings	***Destroyed buildings***
Red	20 - 55	85 - 130
Green	20 - 50	75 - 130
Blue	15 - 35	45 - 85
Near infrared	10 - 30	35 - 60

Table 2. Texture values (Laplace) for spectral bands R, G, B, NIR

Texture parameter	***Texture values***	
	Undestroyed buildings	***Destroyed buildings***
Laplace operator	20 - 55	85 - 130
Laws SL operator	25 - 50	75 - 100
Local curvature	20 - 40	65 - 90
Standard deviation	20 - 40	50 - 75

Table 3. Texture values for different parameters (red)

Texture parameter	***Change of texture values***	
	Undestroyed buildings	***Destroyed buildings***
Laplace operator	5 - 15	35 - 130
Laws SL operator	5 - 20	40 - 100
Local curvature	5 - 20	30 - 70
Standard deviation	5 - 10	30 - 65

Table 4. Change of texture values for undestroyed and destroyed buildings

5.5 Analysis of multi-spectral orthophotos

The aerial image data (R, G, B, NIR) were acquired with a digital aerial camera in the year 2005. The investigations of this study show that this information is just as well useful for our application as the multi-spectral scanner data (cf. section 5.4). The higher resolution may lead to slight negative effects for damage classification compared to the scanner data. Destroyed buildings for instance contain more and larger uniform parts, e.g. plates, oblique walls, etc. which result in decreasing texture values in many cases (Table 5). Due to the lack of additional data from other dates, the variability – especially with respect to undestroyed buildings – may be too optimistic.

Texture parameter	***Texture values***	
	Undestroyed buildings	***Destroyed buildings***
Laplace operator	10 - 25	50 - 90
Laws SL operator	10 - 20	30 - 50
Local curvature	15 - 30	70 - 130
Standard deviation	5 - 10	20 - 40

Table 5. Texture values for undestroyed and destroyed buildings (orthophoto, red)

Figure 3 (c) shows the orthophoto of the same destroyed building illustrated in Figure 3 (b). Figures 3 (f), (i), and (l) show the results obtained by the Laplace operator, the Laws SL operator, and the standard deviation, respectively.

5.6 Classification

For this study only one texture parameter was included into the classification process at a time. For the multi-spectral scanner data the change of texture was used. Since orthophotos were available only for one date, exclusively the absolute texture values could be analysed and included into the classification instead of the change of texture. Both, the change of texture values extracted from the scanner data and the absolute texture values extracted from the orthophotos were determined for each reference roof plane as median of the pixel values assigned to the respective plane.

In order to include the texture information extracted from the multi-spectral images into the classification process, membership functions had to be defined for these new features and each damage type. Therefore, the results of the texture analyses summarised in Table 4 and 5 were transformed into piecewise linear functions.

6. RESULTS

In this section the classification results achieved by using different input data and features are compared and analysed. The following cases are distinguished:

1. ALS data (original method, cf. section 3)
2. ALS data (with improvements described in section 4)
3. ALS data + multi-spectral scanner data
    a. Laplace operator (visible red)
    b. Laws SL operator (visible red)
    c. Local curvature (visible red)
    d. Standard deviation (visible red)
4. ALS data + multi-spectral orthophotos
    a. Laplace operator (visible red)
    b. Laws SL operator (visible red)
    c. Local curvature (visible red)
    d. Standard deviation (visible red)

Besides these different cases for input data introduced into the classification, four different combinations of discriminated classes were investigated:

I. 10 damage types distinguished in (Rehor, 2007) whereas the damage type *heap of debris* was divided into the two damage types *heap of debris* and *heap of debris with vertical elements.*

II. Damage types of case I. whereas the two different types of *pancake collapses* are fused.
III. Damage types of case I. whereas the two different types of *heaps of debris* are fused.
IV. Damage types of case I. whereas both the two different types of *pancake collapses* and *heaps of debris* are fused.

Table 6 shows the overall classification rates of the different combinations of input data and discriminated damage types. It shows that the improvements described in section 4 lead to a significantly higher overall classification rate in comparison to the original classification method. However, the classification results seem not to be improved by integrating multi-spectral data. But it has to be mentioned that the relation of the largest and the second largest degree of match increases in many cases if the classification decision is correct. This implicates a more stable decision for the damage type with the largest degree of match. In contrary, the largest and the second largest degree of match converge in many cases of misclassification. This indicates a less reliable classification decision as in the classification based on ALS data exclusively. In summary this means an increased reliability of the classification result for correct classified segments whereas the reliability is reduced for misclassified ones.

Input data	***Overall classification rate [%]***			
	I.	***II.***	***III.***	***IV.***
1.	-	-	64.3	70.8
2.	77.6	84.9	80.6	87.9
3.a.	77.6	84.9	80.6	87.9
3.b.	77.6	84.9	80.6	87.9
3.c.	77.6	84.9	80.6	87.9
3.d.	77.6	84.9	80.6	87.9
4.a.	77.4	84.7	80.4	87.7
4.b.	77.4	84.7	80.4	87.7
4.c.	77.4	84.7	80.4	87.7
4.d.	77.4	84.7	80.4	87.7

Table 6. Overall classification rates of classifications carried out with different input data and using a different number of damage types

The comparison of the four overall classification rates in each line of Table 6 shows a higher increase for the fusion of the two different types of *pancake collapses* than for the fusion of the two different types of *heaps of debris*. Of course, the highest overall classification rate is obtained if both are fused.

7. CONCLUSIONS

Different possibilities for improving a building damage detection and classification method based originally on ALS data exclusively were presented. One comprises the treatment of pixels not fitting to larger planes in the post-event data which had not been further analysed in the original method. They are now clustered and these clusters are assigned to different damage types afterwards. Another refinement is the introduction of a new feature for identifying vertical elements within heaps of debris.

Moreover, the benefit of including spectral information into the classification was analysed. For this purpose, laser intensity values, multi-spectral scanner data, and high resolution orthophotos were examined. The laser intensities have proved to be unsuitable because of a high variation of texture and its change between different acquisition dates. More appropriate results have been obtained for multi-spectral scanner data and orthophotos. Therefore, different texture parameters derived from these image data were investigated regarding their contribution to the discrimination of undestroyed and destroyed buildings. For this application the Laplace operator, the Laws SL operator, the local curvature and the standard deviation proved to be most suitable.

Finally, the classification method was carried out using different combinations of input data and discriminated damage types. Thus, it was verified that the analysis of clusters of unsegmented pixels can increase the classification rate significantly whereas the integration of additional spectral information does not provide a further improvement of the overall classification rate. However, by integrating spectral texture features the classification results become more reliable.

In future, further investigations should be carried out in order to determine if higher resolution orthophotos can contribute not only to the discrimination of destroyed and undestroyed buildings but also to the distinction of different types of debris heaps. Due to the minor number of damaged buildings, additional data sets have to be analysed in order to stabilise the obtained classification rates.

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REFERENCES

Chesnel, A.-L., Binet, R. and Wald, L., 2007. Quantitative Assessment of Building Damage in Urban Area Using Very High Resolution Images. Urban Remote Sensing Joint Event 2007, Paris, France, 5 pages.

Haralick, R. M., 1979. Statistical and Structural Approaches to Texture. *Proceedings of the IEEE*, Vol. 67, No. 5, pp. 786-804.

Haralick, R. M., Shanmugam, K. and Dinstein, I., 1973. Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-3, No. 6, pp. 610-621.

Rehor, M., 2007. Classification of building damages based on laser scanning data. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Espoo, Finland, Vol. XXXVI, Part 3/W52, pp. 326-331.

Rehor, M. and Bähr, H.-P., 2007. Detection and analysis of building damage caused by earthquakes using laser scanning data. In: Proceedings of the International Symposium on Strong Vrancea Earthquakes and Risk Mitigation, Bucharest, Romania, pp. 457-471.

Rezaeian, M. and Grün, A., 2007. Automatic classification of collapsed buildings using object and image space features. In: Geomatics Solutions for Disaster Management, Lecture Notes in Geoinformatics and Cartography, J. Li, S. Zlatanova, A. Fabbri (eds.), Springer, Berlin, Germany, pp. 135-148.

Sumer, E. and Turker, M., 2006. An integrated earthquake damage detection system. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Salzburg, Austria, Vol. XXXVI, Part 4/C42.

Vu, T. T., Yamazaki, F. and Matsuoka, M., 2007. Context-based detection of post-disaster damaged buildings in urban areas from satellite images. Urban Remote Sensing Joint Event 2007, Paris, France, 5 pages.