VERIFICATION OF A BUILDING DAMAGE ANALYSIS AND EXTENSION TO SURROUNDINGS OF REFERENCE BUILDINGS

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ABSTRACT:

After a disaster not necessarily all buildings in affected areas are damaged. Therefore, a building damage analysis does not only have to distinguish different damage types. In fact, unchanged buildings have to be identified correctly with a high reliability, too. For this purpose, a building damage detection and classification method based on airborne LIDAR data is applied to data of two Swiss villages which did not change between the acquisition dates of pre- and post-event data. The aim is to verify the correct classification of unchanged buildings. The achieved results which are very satisfying are presented in this paper. In its current state, this building damage detection and classification method analyses only changes inside reference building contours. In order to integrate also changes outside the reference building contours into the approach, different preprocessing steps are necessary. One of them – the elimination of vegetation in the post-event LIDAR data – is explained in this paper. It is necessary because remaining vegetation in the surroundings of a building could erroneously be interpreted as debris and might, therefore, cause misclassifications. Different procedures for eliminating vegetation are described. Investigations showed that their suitability depends on the vegetation's foliation state. Thus, in summer when trees are leafy it is very helpful to have additional multispectral data. In this case, the Normalised Difference Vegetation Index (NDVI) in combination with the near infrared can be used. In winter, when trees are bare and, therefore, at least partially penetrable for the laser beam differences of first and last echo LIDAR data proved to be suitable.

1. INTRODUCTION

After a disaster like an earthquake, people are often trapped in collapsed buildings and have to be rescued. A building damage analysis identifying the damage types of buildings can support search and rescue teams in using the available resources as efficiently as possible. The correct classification of unchanged buildings is essential for such a damage analysis. For detecting different damage types, pre-event building models can be compared to post-event data. It is assumed that the reference data set contains no 3D objects except the reference buildings. Therefore, the post-event data should also contain only buildings, building parts and debris caused by collapsed reference buildings because other objects like vegetation or cars located near a reference building could erroneously be considered as debris and cause a misclassification of the building's damage type.

For this reason, one important aspect is to eliminate the vegetation from the original post-event data. The topic of detecting vegetation in airborne laser scanning (ALS) and multispectral data was often investigated in the last years. Therefore, many publications exist and a brief overview is given here. Approaches based exclusively on LIDAR data utilise parameters indicating surface roughness (Brunn and Weidner, 1998), height texture (Maas, 1999), differences of first and last echo data or laser intensity (Tóvári and Vögtle, 2004). In contrast to this, multispectral data can be used. In this case, the Normalised Difference Vegetation Index (NDVI) is a frequently employed parameter if near infrared (NIR) data are available (Vögtle and Steinle, 2000). If only an RGB image is available, Bretar and Chehata (2007) propose a Hybrid-NDVI calculated by substituting the NIR value of an optical image by the LIDAR intensity. Moreover, some approaches use features extracted from both LIDAR height data and multispectral data (Rottensteiner et al., 2005; Matikainen et al., 2007).

For the verification process, an existing building damage detection and classification method (Rehor, 2007; Rehor and Voegtle, 2008) based on ALS data is applied to data of two unchanged villages. A problem of this building damage analysis is the missing extension on the areas around the reference buildings contained in the pre-event data. For integrating the surroundings of these reference buildings additional features like the increase of volume within buffers around the reference buildings have to be determined (Hommel, 2009), for example by adding the volumes of all objects located within these buffers in the post-event data. As mentioned above, vegetation has to be eliminated from the post-event data in this case. Otherwise, vegetation objects located within the buffer around a reference building which are considered as debris would cause a non-existing increase of volume. This in turn could result in misclassifications since this volume increase would support the decision for particular damage types and contradict other ones. In this case, it might be possible that the correct damage type is excluded because of the misconceived increase of volume. Due to similar characteristics of vegetation and debris (surface roughness), the techniques listed above cannot necessarily be used without adaption for distinguishing them.

In order to describe the verification of the building damage analysis and possibilities for eliminating vegetation from post-disaster data, the paper is structured as follows. In Section 2 the used data are described. Section 3 contains a short summary of the tested damage classification method and the presentation and analysis of the achieved results. Different possibilities for discriminating vegetation and debris using different features like NDVI, reflectance values in NIR, or differences of first and last echo measurements are described in Section 4. In Section 5 the results of the verification process are summarised and the dependency of the suitability of the methods for eliminating vegetation on the foliation state of trees and bushes is discussed.

2. DATA

For the development of the building damage detection and classification method, ALS data of the test site 'Epeisses' were

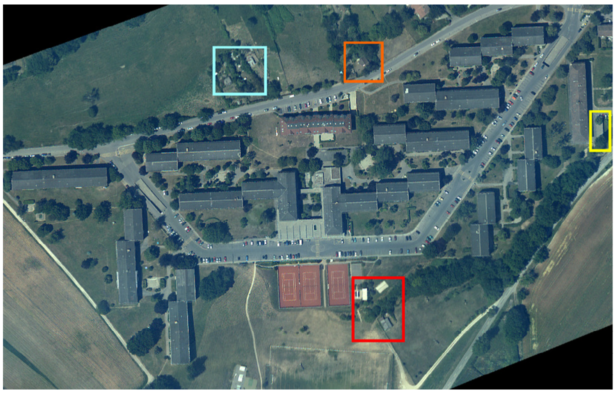


Figure 1. Multispectral scanner image (RGB, June) of Gennecy.

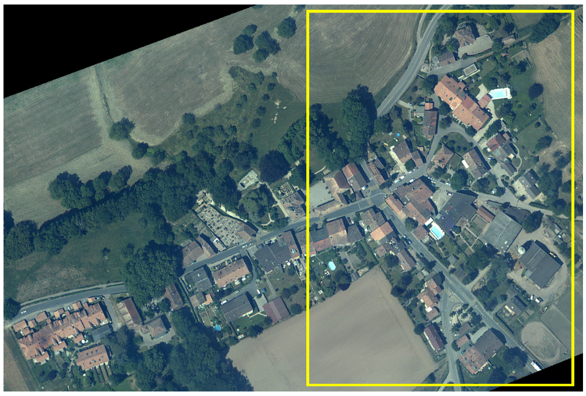


Figure 2. Multispectral scanner image (RGB, June) of Avully.

acquired – a training area of the *Swiss Military Disaster Relief* located close to Geneva which contains several undamaged and damaged buildings. Therefore, two flights were carried out using the TopoSys (Germany) Falcon II system – the first in June 2004, the second in November 2004. The point clouds were interpolated in a raster with 1 m pixel size. Moreover, the influence of the terrain was removed by generating normalised digital surface models (nDSM). During each flight multispectral data (0.5 m pixel size on ground) were acquired simultaneously with the RGB/NIR line scanner integrated in Falcon II in four spectral bands (B: 450-490 nm, G: 500-580 nm, R: 580-660 nm, NIR: 770-890 nm).

Additionally to the test site 'Epeisses' there are two villages lying within the acquired area – Gennecy and Avully. In Gennecy there are especially larger houses with gable roofs which are arranged very regularly (Figure 1). Most of these buildings have no dormers and there are also only few small buildings like garages or sheds. In contrary, Avully mainly consists of smaller houses with many dormers (Figure 2). Furthermore, there are many small garages and sheds. Moreover, the buildings are not regularly arranged and their shape is often not a simple rectangle (i.e. adjacent walls are not necessarily perpendicular).

3. APPLICATION OF A BUILDING DAMAGE ANALYSIS TO UNCHANGED AREAS

3.1 Building damage detection and classification method

The building damage detection and classification method verified in this contribution was presented in detail in Rehor (2007) and Rehor and Voegtle (2008). Therefore, only a short summary will be given here.

In order to detect and classify changes in building geometry, pre- and post-event data are compared. Therefore, it is assumed that reference building models or at least their roof planes exist. In a first step, planar surfaces are extracted from nDSMs derived from post-event ALS data. These planar surfaces and their corresponding roof planes of the reference buildings are superposed. In this way, new segments are created on which the fuzzy logic classification can be based on using the features *volume* and *height reduction*, *change of inclination*, and *size*. In this approach eleven 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, heap of debris with vertical elements*, *overturn collapse (separated)*, and *inclination*. For the distinction between *heaps of debris* with and without vertical elements the standard deviation of the segment's median filtered height texture values determined with the Laplace filter is used. 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. These pixels are clustered and afterwards these clusters are also classified using the *volume reduction*, the *minimum height difference*, and the *contrast* of the segment's height values as features. In this case, only five classes are distinguished: *unchanged*, *heap of debris on uncollapsed storeys*, *heap of debris*, *heap of debris with vertical elements*, *destroyed with preserved roof structure*.

After creation of segments and clusters – but before the classification step – segments smaller than 20 % of the average segment size of the current building are merged with the largest neighbouring segment or cluster. This procedure solves the problem of misclassification of small segments among otherwise correctly classified segments (Rehor, 2007) at least partially. In order to optimise the results, a new step is carried out now. After classification of segments and clusters a statistic of the occurring damage types is calculated for each building. If one damage type makes up less than a given minimum percentage of a building's footprint (in this study 5 %), it is merged with that damage type having the longest edge with it.

3.2 Results

In order to verify that the described building damage detection and classification method works well for unchanged areas, it was applied to the data of the two villages Gennecy and Avully. The visual comparison of the multispectral scanner data for the two acquisition dates shows no major changes for the existing buildings.

The reference buildings were extracted from the ALS data acquired in June 2004 using the method described in Vögtle and Steinle (2000). As exclusively the roof planes of the reference buildings are necessary for the comparison with the post-event data, no complete 3D building models were generated. In fact, only their roof planes were determined from the ALS data with the region growing algorithm for automatic plane detection described in Rehor et al. (2008).

Overviews over the results achieved before and after the new postprocessing step described in Section 3.1 are given in Table 1 and Table 2. They show that most of the buildings are classified as *unchanged*. In Gennecy all larger residential buildings are classified correctly. Misclassifications occur only for small buildings representing garages, summerhouses, or sheds (cf. Figure 3). This can be explained by slight displacements in the post-event data (compared to the reference

Damage type	*Before new step*		*After new step*	
	Area (m²)	*Percen-tage*	*Area (m²)*	*Percen-tage*
Unchanged	15621	95.86 %	16219	99.53 %
Inclined plane	339	2.08 %	4	0.02 %
Heap of debris	154	0.95 %	23	0.14 %
Heap of debris with vertical elements	71	0.44 %	15	0.09 %
Destroyed with pre-served roof structure	99	0.61 %	34	0.21 %
Inclination	2	0.01 %	0	0.00 %
Unclassified	10	0.06 %	1	0.01 %

Table 1. Classification results for Gennecy.

data) due to the sensor, the terms of acquisition, and the raster interpolation. These cause height and volume differences at the building borders. Hence, these regions are often classified as *heap of debris* or *heap of debris with vertical elements*. For large buildings these misclassified regions make up a very small percentage referring to the area of the whole building. Thus, they are merged with the main damage type of the building during the new postprocessing step (cf. Section 3.1). Another damage type occurring in Gennecy is *destroyed with preserved roof structure*. The reason is that for small buildings often no planar surfaces exceed a given minimum size (here 3 m × 3 m). Therefore, many pixels of small buildings remain unsegmented. They are clustered and analysed as such clusters. If the volume or minimum height reduction is a little bit too large – for example due to pixels at the building edge for which the effect described above occurs – the segment is classified as *destroyed with preserved roof structure* instead of as *unchanged*.

In Avully there are more misclassifications than in Gennecy (cf. Figure 4) due to a completely different architecture of the buildings. The large amount of dormers causes many unsegmented pixels during the extraction of planar surfaces. Thus, the effect occurs which appeared in Gennecy for small buildings only. Furthermore, the roof planes in Avully are mostly smaller or interrupted by dormers, so planar surfaces cannot be estimated as reliably as they would be if they were covered by more points. This causes minor changes in inclination of corresponding pre- and post-event planes and, therefore, the discrimination between damage types *unchanged* and *inclined plane* is impaired.

Altogether the results for the two test sites Gennecy and Avully are very satisfying. It was verified that unchanged buildings can be identified very reliably with the current building damage detection and classification method only analysing the situation within the contours of reference buildings. As some damage types cannot be identified if changes outside the reference building contour are not taken into account, the following procedure is suggested for a fast damage analysis: The current classification method is used to determine if a building has changed or not. The buildings classified as *unchanged* by this method are eliminated from further analysis. Afterwards, all other buildings are examined in more detail including their surroundings in order to identify their correct damage types.

4. ANALYSIS OUTSIDE BUILDING CONTOURS

For extending the analysis to changes outside the reference building contours (Hommel, 2009), the vegetation has to be eliminated from the post-event data first. Otherwise, increases of volume caused by vegetation could lead to wrong

Damage type	*Before new step*		*After new step*	
	Area (m²)	*Percen-tage*	*Area (m²)*	*Percen-tage*
Unchanged	14808	93.17 %	15379	96.76 %
Inclined plane	286	1.80 %	98	0.62 %
Multi-layer collapse	49	0.31 %	4	0.03 %
Heap of debris	185	1.16 %	69	0.43 %
Heap of debris with vertical elements	478	3.01 %	340	2.14 %
Destroyed with pre-served roof structure	49	0.31 %	4	0.03 %
Inclination	2	0.01 %	0	0.00 %
Outspread multi-layer collapse	1	0.01 %	0	0.00 %
Pancake collapse of one storey	2	0.01 %	0	0.00 %
Unclassified	34	0.21 %	0	0.00 %

Table 2. Classification results for Avully.

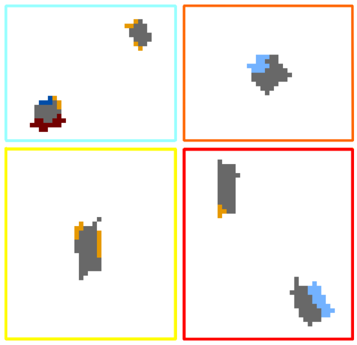


Figure 3. Partially misclassified buildings of test site Gennecy (colours of frames correspond to the rectangles in Figure 1; legend: grey: *unchanged*, dark blue: *inclined plane*, green: *multi-layer collapse*, orange: *heap of debris*, dark red: *heap of debris with vertical elements*, light blue: *destroyed with preserved roof structure*).

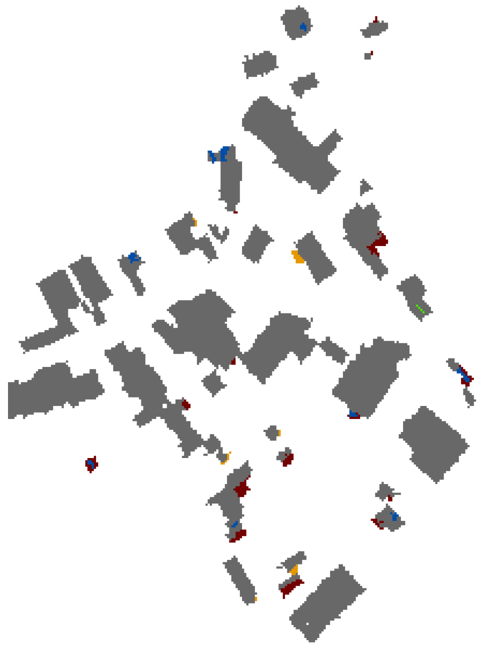


Figure 4. Subset of classification results (yellow rectangle in Figure 2) for test site Avully (legend cf. Figure 3).

assumptions and consequently result in misclassifications (cf. Section 1). In the following subsections different possibilities are described for eliminating vegetation from post-disaster data depending on the available data types and the vegetation's state of foliation. Subsection 4.1 acts on the assumption that multispectral data are available whereas in Subsection 4.2 only lidar data are used. The data acquired in June were obtained under leaf-on conditions, the data acquired in November under leaf-off conditions. The problem of classifying vegetation in post-disaster data in contrary to non-disaster data are the similar characteristics of debris and vegetation in some cases (e.g. concerning their surface roughness).

4.1 Using multispectral data

The restriction of multispectral data for detecting vegetation is the fact that it cannot always be acquired during a laser scanning flight. As laser scanning is an active measurement technique, it has the big advantage that data can be acquired independently of time of day. Multispectral data in contrary can only be acquired in the daytime what is a major limitation.

4.1.1 Leaf-on conditions: In case of leafy trees and available multispectral data the $NDVI = (NIR - R) / (NIR + R)$ can be used to detect vegetation, where *NIR* represents the value of the near infrared channel and *R* the value of the red channel. The *NDVI* is based on the characteristics of leaves which have a high reflectance in the near infrared and a low one in the visible red. Therefore, the *NDVI* has high values for vegetation and small values for other materials. Furthermore, in shadow regions also high values are obtained for the *NDVI* since *NIR* as well as *R* are small. Hence, an additional condition has to be used for distinguishing vegetation and shadows: Not only the *NDVI* has to be greater than a given threshold t_{NDVI} but also the *NIR* has to be greater than another threshold t_{NIR}.

As example, Figure 5a shows a colour infrared (CIR) image of a building and five trees acquired in June. In Figure 5b the *NDVI* values for this subset are calculated: The brighter the grey value of a pixel the higher is its *NDVI*. Figure 5b shows very clearly that shadow areas also have a high *NDVI*. Figure 5c illustrates a binary image achieved for $t_{NDVI} = 0.176$ and $t_{NIR} = 60$, i.e. black pixels fulfil both conditions: $NDVI > t_{NDVI}$ and $NIR > t_{NIR}$. The values of t_{NDVI} and t_{NIR} were determined experimentally. Obviously, the trees are very well detected in these data. In order to eliminate the single separated vegetation pixels and to close wholes within trees, mathematical morphology is used (here: an opening followed by a closing). This means that the black regions are firstly eroded, afterwards dilated twice and then eroded again. The result of this processing step is the vegetation mask shown in Figure 5d.

4.1.2 Leaf-off conditions: As mentioned above, the *NDVI* is not suitable if there are no leaves on the trees and bushes. This gets clear with the following example.

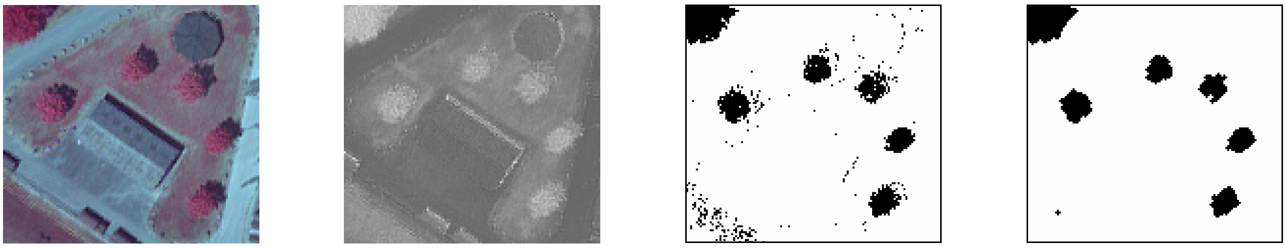
The CIR image illustrated in Figure 6a is taken from the same subset as Figure 5a but for the leaf-off data acquired in November. Analogue to Figure 5, Figure 6b, 6c, and 6d contain the *NDVI*, the binary image obtained with the same thresholds t_{NDVI} and t_{NIR} as in Section 4.1.1, and the vegetation mask after applying morphological filters, respectively. In Figure 6b the trees are darker than the surrounding grass implying that their *NDVI* is less than the *NDVI* of the grass. Figure 6c and Figure 6d show that not both *NDVI* and *NIR* exceed the given thresholds t_{NDVI} and t_{NIR} for the trees. Therefore, the trees are not identified as vegetation by this method.

4.1.3 Conclusion: The comparison of Figure 5 and Figure 6 makes clear that the combination of *NDVI* and *NIR* is very suitable for the elimination of vegetation if multispectral data are available under leaf-on conditions. In contrary, this method cannot be used in case of bare trees and bushes.

4.2 Using differences of first and last echo data

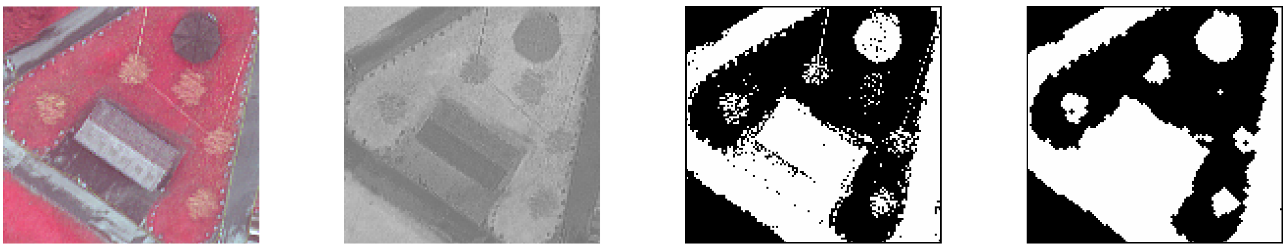
As mentioned in Section 4.1, multispectral data are not always available for eliminating vegetation and, moreover, they cannot be used in case of defoliated vegetation. Hence, another method was investigated using only first and last echo LIDAR data.

The use of differences between first and last echo measurements for distinguishing vegetation from buildings works well because roofs normally are continuous and not penetrable by ALS. Hence, only small first/last echo differences occur inside



a b c d

Figure 5. a) Multispectral scanner image (CIR) of a building and 5 trees acquired in June; b) *NDVI* of a); c) binary image: black: $NDVI > 0.176$ and $NIR > 60$; d) vegetation mask derived from c) by applying mathematical morphology.



a b c d

Figure 6. a) Multispectral scanner image (CIR) of a building and 5 trees acquired in November; b) *NDVI* of a); c) binary image: black: $NDVI > 0.176$ and $NIR > 60$; d) vegetation mask derived from c) by applying mathematical morphology.

building contours. Vegetation in contrary is often at least partially penetrable for laser beams and, therefore, first/last echo differences are large. Of course, along building borders there are also large first/last echo differences, but for vegetation they occur rather area-wide. For identifying vegetation by means of first/last echo differences the following procedure is used. Firstly, an image containing the first/last echo differences is binarised using a threshold t_{FLE} where all pixels exceeding this threshold are classified as foreground. Secondly, for eliminating single or linearly arranged pixels caused by building borders or other small objects, two morphological operations are carried out namely an opening followed by a closing (cf. Section 4.1.1).

However, if there is debris the situation is more complicated because e.g. for single still standing walls the first/last echo differences are also large. And if there are several such walls within the area of a building, the first/last echo differences are also large across the area. For this purpose, the assumption is made that there is no vegetation within the reference building contours. Therefore, the reference buildings are masked out in the first/last echo difference image. Outside the reference building contours there are usually no remaining walls or building parts causing area-wide large first/last echo differences because walls are typically overturned if they occur beyond the original building contour. Heaps of debris located outside building footprints are normally rather convex-shaped. Therefore, no larger height differences caused by debris appear area-widely outside reference building contours. Figure 7 shows an example. Figure 7a and 7b contain the RGB images of an area with a damaged building and a tree acquired in June and November, respectively. Except Figure 7a, all other images of Figure 7 refer to the data acquired in November. The RGB image of June was integrated due to a better recognisability of the tree. Figure 7c and 7d visualise the first and last echo data. In Figure 7e the first/last echo differences can be seen. Figure 7f also shows the first/last echo differences, but in this case the reference buildings are masked out. Carrying out a binarization of Figure 7f using t_{FLE} = 1.00 m results in Figure 7g. The final vegetation mask in Figure 7h is obtained by applying the morphological operations described above.

Another problem occurring if only fist/last echo differences are used is the non-reliable penetration of dense vegetation by the laser beam (leaf-on). If there are leaves on the trees and bushes, it is reflected completely at the treetop and does not reach the lower tree parts or the ground. Hence, the first/last echo differences are small and, therefore, some trees are not detected as vegetation (Figure 8). In contrary, leaf-off data in which vegetation is bare produced quite satisfying results (Figure 9).

5. CONCLUSION

In order to verify the results for unchanged buildings, a building damage detection and classification method was applied on ALS data of two unchanged villages. The results achieved are very satisfying since classification rates of about 99 % (regularly arranged buildings) and 96 % (irregularly arranged buildings) were obtained.

Different methods for identifying vegetation in post-event LIDAR data were described. The elimination of vegetation is necessary if the situation around a reference building is integrated into the damage analysis. The investigations showed that a combination of *NDVI* and *NIR* is very suitable in case of available multispectral data and foliated vegetation. If the vegetation is defoliated, the use of first/last echo differences proved to be more suitable. These were only some first approaches on this topic. In future, further studies should be carried out with the objective to find adaptive approaches which can be used depending on the available data (only LIDAR or also multispectral) and the vegetation's state of foliation. Also the combination of both multispectral and LIDAR data may be used to distinguish vegetation and debris in a better way. Or it might be suitable to carry out a segmentation first and classify these segments afterwards.

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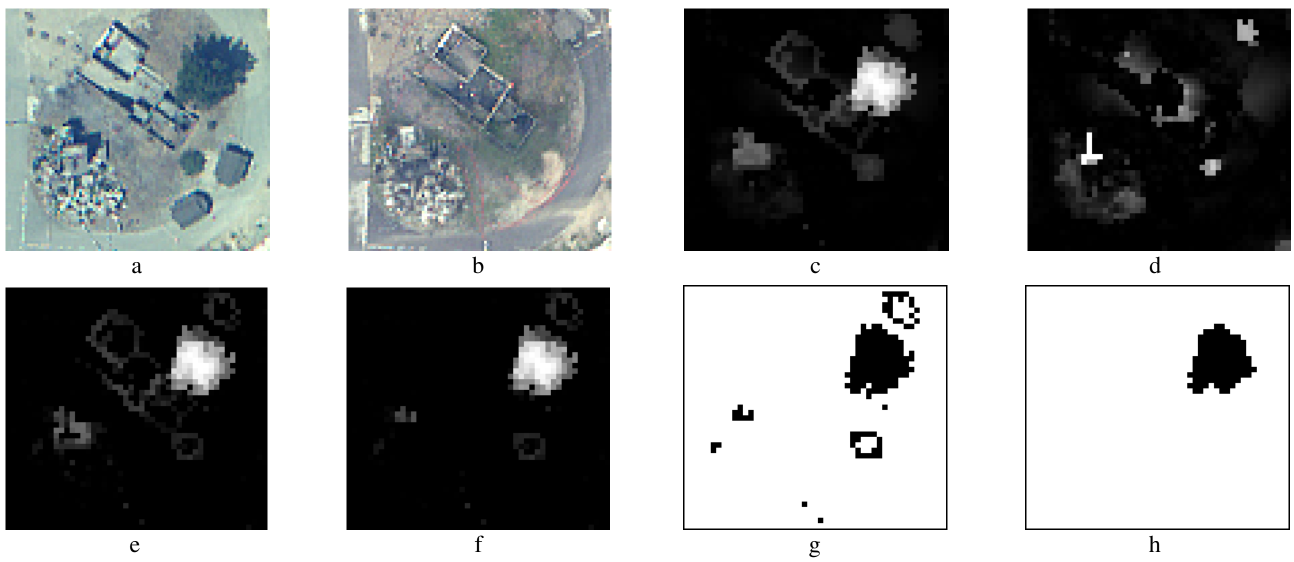

Figure 7. a) Multispectral scanner image (RGB) of a tree (top right) and a damaged building (down left) acquired in June; b) RGB image of the same subset as in a) acquired in November; c) first echo data of November; d) last echo data of November; e) first/last echo differences of November data; f) first/last echo differences of November data where buildings are masked out; g) binary image: black: first/last echo difference of f) > 1.00 m; h) vegetation mask derived from g) by applying mathematical morphology.

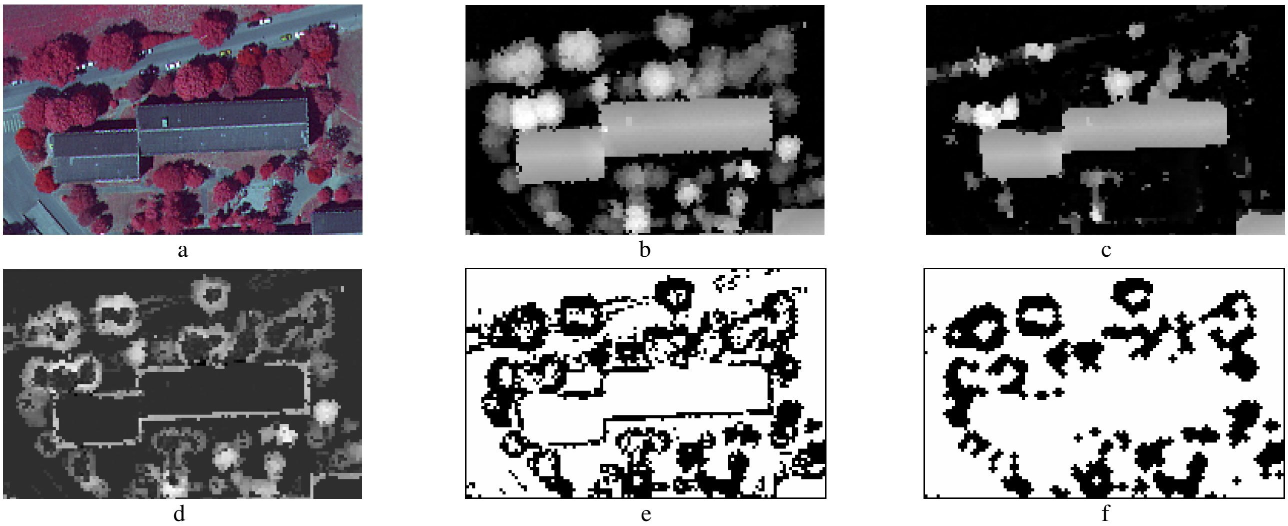

Figure 8. a) Multispectral scanner image (CIR) of a building and several trees acquired in June; b) first echo data; c) last echo data; d) differences of first and last echo data; e) binary image of d): black: (first echo – last echo) > 1.00 m; f) vegetation mask derived from e) by applying mathematical morphology.

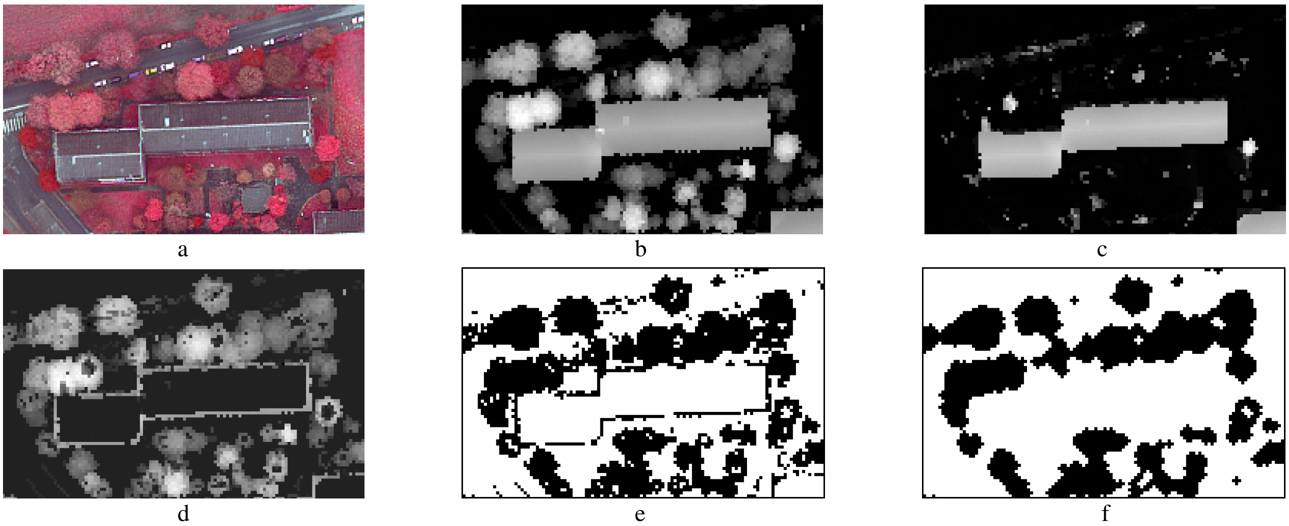

Figure 9. a) – f) correspond to cases in Figure 8 but for the data acquired in November.

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