AIRBORNE LIDAR AS A TOOL FOR DISASTER MONITORING AND MANAGEMENT

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ABSTRACT:

Airborne and terrestrial lidar are rapid and accurate techniques for remote measurement of terrain elevations with many applications, such as for digital terrain elevation measurement, volume determination, assessment of forest resources, coastal land erosion and many more. For disaster monitoring, typical examples of airborne lidar are flood prediction and assessment, monitoring of the growth of volcanoes and assistance in the prediction of eruption, assessment of crustal elevation changes due to earthquakes, and monitoring of structural damage after earthquakes. Change detection is an important task in the context of disaster monitoring. The paper will describe the capability of airborne lidar for rapid change detection in elevations, and methods of assessment of damage in made-made structures. The idea is to combine change detection techniques with different performance based on Simple Majority Vote. In order to detect and evaluate changes, a DEM of two epochs has been used. The analysis of changes is rather difficult to evaluate if only one detection model is applied. In this regard, three different change detection algorithms were used to detect changes. The used techniques include: Image Differencing, Principal Components Analysis (PCA) and post-classification with average detection accuracies of 84.7%, 88.3% and 90.2% for post-classification, Image Differencing and PCA respectively. Simple Majority Vote was then applied for combining votes from the three detection techniques. The proposed fusion algorithm gives an accuracy of 96.4%**.** This activity demonstrates the capabilities of lidar data to detect changes, providing a valuable tool for efficient disaster monitoring and effective management and conservation.

1. INTRODUCTION AND RELATED WORKS

An up-to-date building database is a crucial requirement for a reliable damage assessment. Change detection employing lidar data could be useful for damage detection, particularly for collapsed multi-floored buildings (Tuong et al., 2004). Lidar (Light Detection and Ranging) is equipped with a laser scanner, a Global Positioning System (GPS) receiver and an Inertial Navigation System (INS). It is an active sensor which emits infrared laser pulses at high frequency and records the time of transmission of the return pulses, resulting in the determination of X, Y and Z coordinates of ground points at frequencies of 1point or more per m^2. The intensity of the return laser pulses can also be recorded. There are basically two types of laser scanning systems: discrete laser and waveform. A discrete signal is emitted from the laser and one or more return signals are recorded. Waveform systems record the full waveform of the return signal.

Methods of change detection can mainly be divided into two categories:

- The determination of the difference of classifications of a surface obtained at two periods;
- The direct determination of change between two data sets.

Detecting changes by supervised classification is unreliable when the appearance of non-buildings and buildings are similar. Furthermore, using spectral information to detect change does not consider the situation when the differences occur in shape instead of colour (Huang and Chen, 2007). A number of researchers, such as Knudsen and Olsen (2003), Matikainen et al. (2004), Walter (2004a) and Walter (2004b) belonged to the first category above. The second category [Murakami et al., 1999; Jung, 2004] is unable to determine the land category because no classification is used. It is also observed that trees often cause mistakes in the output of research.

Even though aerial photograph has been conventionally employed for change detection [Niederöst, 2001; Knudsen and Olsen, 2003; Walter, 2004a; Walter, 2004b], aerial photograph causes several unavoidable problems such as: shadows in the scenes acquired over dense urban areas with many skyscrapers; the spectral information of certain features in aerial photographs is diverse and ill-defined (Knudsen and Olsen, 2003); perspective projection causes relief displacement of buildings, which requires the height information to correct. Therefore, the employment of lidar rather than spectral information derived from aerial photographs offers important advantages (Tuong, et al., 2004). It allows obtaining 3D points of the surface with high density as well as high accuracy. Moreover, the method is capable to collect data of large areas in a short time (Baltsavias, 1999).

Instead of the multi-spectral imagery that was often used in the past, many change detection methods using lidar data have been proposed. Murakami et al., (1999) carried out change detection of buildings using lidar data in Japan. That study was a simple

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comparison between two data sets. Tuong et al., (2004) presented an automatic method for lidar-based change detection of buildings in dense urban areas. Walter (2004b) used lidar data in an object-based classification to determine the land-use category after the observation of land phenomena. Matikainen et al. (2004) divided a lidar point cloud into homogeneous areas, and then extracted information to discover the building areas for change detection. Girardeau-Montau et al. (2005) directly used point-to-point position relations for change detection. Huang and Chen (2007) included lidar data and aerial images to detect the changes of building models. Brzank et al., (2009) presented a new method to detect and evaluate morphologic changes of the Wadden Sea based on the extraction of structure lines of tidal channels from lidar data. Chien and Lin (2010) developed a new method, namely double threshold strategy, to find changes within 3-D building models in the region of interest with the aid of lidar data. Their modelling scheme comprises three steps, namely, data pre-processing, change detection in building areas, and validation. Research findings clearly indicate that the double-threshold strategy improves the overall accuracy from 93.1% to 95.9%.

It is worth mentioning that, as change detection is an important step in data updating, some methods used spectral-based methods such as the Iterative Principal Components Analysis (IPCA) to determine temporal distance in feature space and combine it with a Bayesian decision rule to determine the presence of change (Spitzer *et al.*, 2001). Clifton (2003) describes training neural networks to learn expected changes between images and to then identify pixel changes which do not match what is "expected". Some other methods used the multi-temporal high-resolution imagery, to detect changes by the spectral difference or use supervised classification to discover the building position to carry out a comparison for change detection (Knudsen and Olsen, 2003).

This paper describes a proposed workflow for lidar-based change detection. The paper is organised as follows. Section 2 describes the study areas and data sources. Section 3 describes the experiments while Section 4 presents and evaluates the results. We summarise our results in Section 5.

2. STUDY AREAS AND DATA SOURCES

In order to demonstrate the capability of the proposed change detection method, two lidar data sets acquired over Tokyo, which is an earthquake-prone area in Japan, on different occasions, were available. Both surveying flights were carried out by Asia Air Survey Co. Ltd in June 1999 and February 2004. Data was provided in 1-m grid format over a dense urban area which includes residential buildings, large buildings, a network of main and local roads, open and green areas as well as trees. Figure 1 shows the acquired lidar data in grid format.

In order to accurately evaluate the performance of the proposed change detection method, changes were visually interpreted and digitized independently of their size as shown in figure 2. It is worth mentioning that the test areas have been used in previous studies (Tuong et al., 2004) for change detection, which used a simple method to form the difference image based on a histogram thresholding and different reference data. The results showed 55% error in detecting new demolitions.

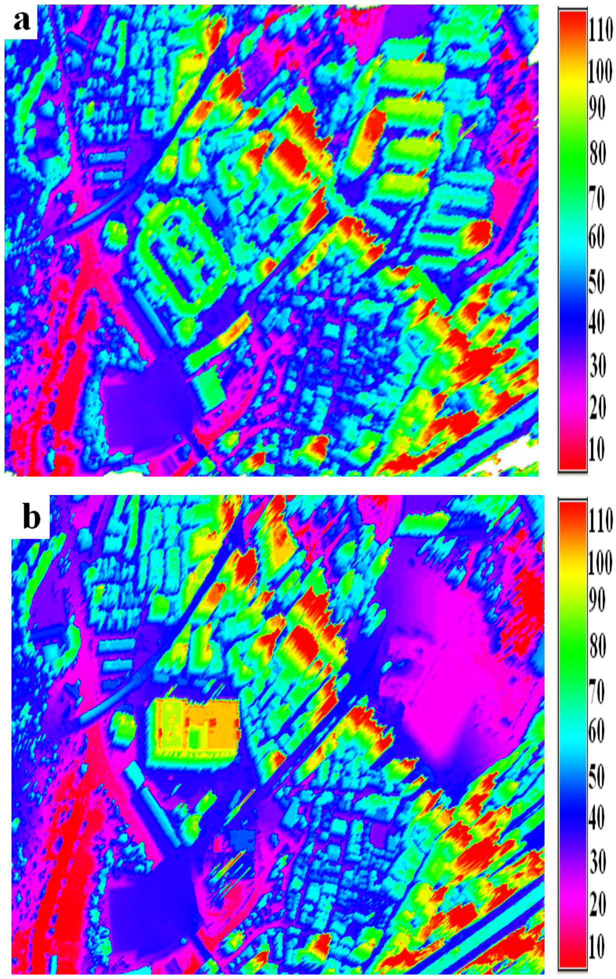

Figure 1. Acquired lidar data in grid format a) June 1999, and b) February 2004.

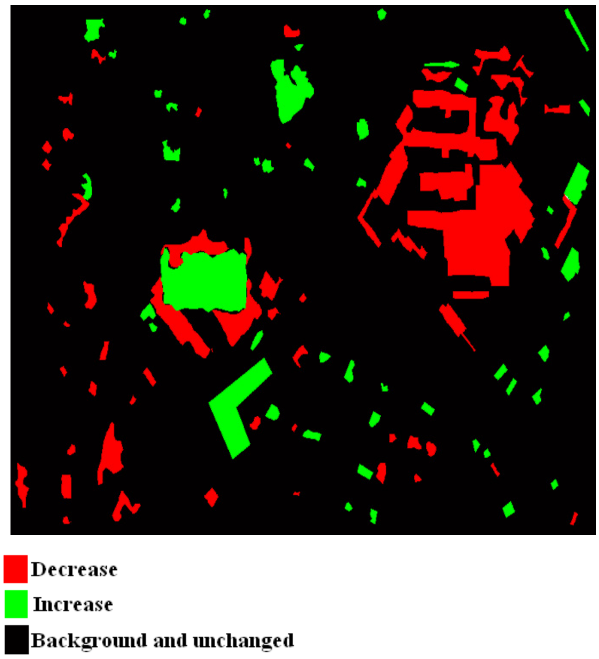

Figure 2. Manually digitized reference changes.

3. METHODOLOGY

3.1 Pre-processing

First, both DEMs were registered to each other based on a projective transformation. The registration process resulted in small Root Mean Square (RMS) errors that did not exceed 0.15m in both X and Y directions. Following the transformation, the images were resampled to 1m pixel size. In order to obtain a high image quality and to reduce the processing time, a bilinear interpolation was applied for the resampling process.

3.1 Main-processing

Three different change analyses were performed to evaluate the efficacy of lidar data for detecting changes occurring at different temporal scales. The three methods include: Image Differencing; Principal Components Analysis (PCA); and Post-Classification based on Support Vector Machine (SVM). After these steps, a Simple Majority Vote has been applied to generate the change detection Image. All the methods proposed in this research were implemented through programs generated by the authors in Matlab environment. An interface was developed to enable the user to: detect changes through the aforementioned three methods; combine votes derived from all methods; generate a change detection image; and evaluate change detection results. The workflow for this investigation is shown in figure 3.

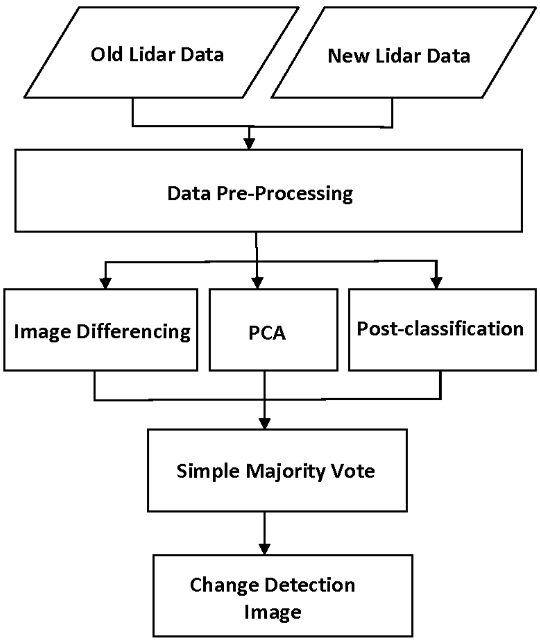

Figure 3. The workflow for the proposed change detection method.

In the first change detection technique, differences between the two DEM images that exceed a user-specified threshold of 10 pixels were computed and highlighted. In the image differencing method, the second image is subtracted from the first image to provide the image difference and highlight changes. The second image is the more recent image and reflects changes over time. After application of image differencing, increases in brightness values that are more than the predefined threshold, are highlighted as increases in height, while decreases in brightness values that are more than the predefined threshold, are highlighted as decreases in height. The result is a grey scale image composed of a single band of continuous data that reflects the changes. The change image is a four-class thematic image, typically divided into the four categories of: background; decreased, increased; and unchanged. Although the calculation is simple, the interpretation requires knowledge about the area, because every difference relates to a certain location but not necessarily to the same object.

In the second change detection technique, Principal Components Analysis (PCA) has been applied to detect changes. Principal Components analysis (PCA) is commonly applied for orthogonal data transformations. PCA maximizes the spectral variability detected by decreasing the redundancy of information contained in multiple spectral bands (Armenakis et al., 2003). PCA components are based on statistical relationships that are difficult to interpret, and are variable between different landscapes and different dates for a single landscape (Collins and Woodcock 1994). PCA is a linear transformation of the data along perpendicular axes of maximum variance between data sets (Legendre and Legendre 1998). The first eigenvector sorts pixels along an axis of highest correlation between data sets. Pixels on this axis have not significantly changed between the two images. The second eigenvector is perpendicular to the first, and therefore sorts pixels that represent differences between data sets.

In the third change detection technique, post-classification comparison was performed in order to detect changes. The two DEM images were classified using Support Vector Machine classifier (SVM), then the classification results were compared and the differences were extracted. The objective is to classify the input data into four primary classes of interest, namely buildings, trees, roads, and ground. SVMs are based on the principles of statistical learning theory (Vapnik, 1979) and delineate two classes by fitting an optimal separating hyperplane (OSH) to those training samples that describe the edges of the class distribution. As a consequence they generalize well and often outperform other algorithms in terms of classification accuracies. Furthermore, the misclassification errors are minimized by maximizing the margin between the data points and the decision boundary. Since the One-Against-One (1A1) technique usually results in a larger number of binary SVMs and then in subsequently intensive computations, the One-Against-All (1AA) technique was used to solve for the binary classification problem that exists with the SVMs and to handle the multi-class problems. The Gaussian radial basis function (RBF) kernel has been used, since it has proved to be effective with reasonable processing times in remote sensing applications.

Then, a simple majority vote, which can be effective than more complex voting strategies, is used to generate the final result. If change detection algorithm c_n assigns a given pixel to class label ω_k, then we say that a vote is given to ω_k. After counting the votes given to each class label by all detection algorithms, the class label that receives a number of votes higher than others is taken as the final output:

$$s_{\mathrm{i}}(x) = \sum_{\substack{j=1 \\ j \neq i}}^{j} sgn\left(f_{\mathrm{ij}}(x)\right) \tag{1}$$

When the three detection methods give completely different decision for a given pixel, which does not convey any information, the decision from the method with highest detection accuracy is considered.

As a last step, the smaller detected regions were merged into larger neighbouring homogeneous ones or deleted according to an arbitrary 1m distance and $30m^2$ area thresholds respectively. The area threshold represents the expected minimum change area, while the distance threshold was set to 1m to fill in any gaps within the detected region. Regions were retained if they were larger than the given area threshold and/or were adjacent to a larger homogeneous region by a distance less than 1m. Finally, region borders were cleaned by removing structures that were smaller than 5 pixels and that were connected to the region border. There was a compromise between cleaning thresholds less than 5 pixels, which may leave the original buildings uncleaned, and thresholds greater than 5 pixels which may remove parts of the detected region. The result was an image that represents the detected changes without noisy features and also without holes.

3.2 Evaluation of the change detection results

The overall accuracy for the detection process was assessed using the reference data and based on equation 2:

$$ODA = \frac{NCP}{NRP} \tag{2}$$

Where *ODA* is the overall detection accuracy; *NDP* is the total number of correctly detected pixels and *NRP* is the total number of reference pixels. On the other hand, in order to evaluate the performance of the change detection process, the *completeness* and the *correctness* (Heipke et al., 1997) of the detected changes were investigated based on a per-pixel as follow:

$$Completeness = \frac{TP}{TP + FN} \tag{3}$$

$$Correctness = \frac{TP}{TP + FP} \tag{4}$$

TP denotes to the number of true positives which is the number of entities that were automatically detected and were available in the reference data. *FN* relates to the number of false negatives which is the number of entities that were available in the reference data but not automatically detected. *FP* stands for the number of false positives which is the number of entities that were automatically detected but do not correspond to any entities in the reference data (Rottensteiner et al., 2007).

4. RESULTS AND ANALYSIS

Figure 4 is a typical example shows the results in a sub-area of the whole test area. For the detected changes, the green colour indicates an increase, the red colour labels a decrease while black colour refers to both background and unchanged. It can clearly be seen that the important changes occur in buildings. In the middle of the area the large building has been replaced with a new one with a different shape. At the lower right part of the area, some new buildings have been constructed.

Another aspect of interest is where the misclassified pixels were recovered by the combination process. Most corrections occur at the edges of buildings and trees, which demonstrates the effect of between-class variance on the edge pixels which caused many of these pixels to be placed in an incorrect category. It can clearly be seen that the detected changes for PCA are eroded as compared to the reference data. This trend can also be observed for post-classification results. On the other hand, the detected changes for image differencing are larger. However, the erosion effect has been reduced after applying the Simple Majority Vote combination.

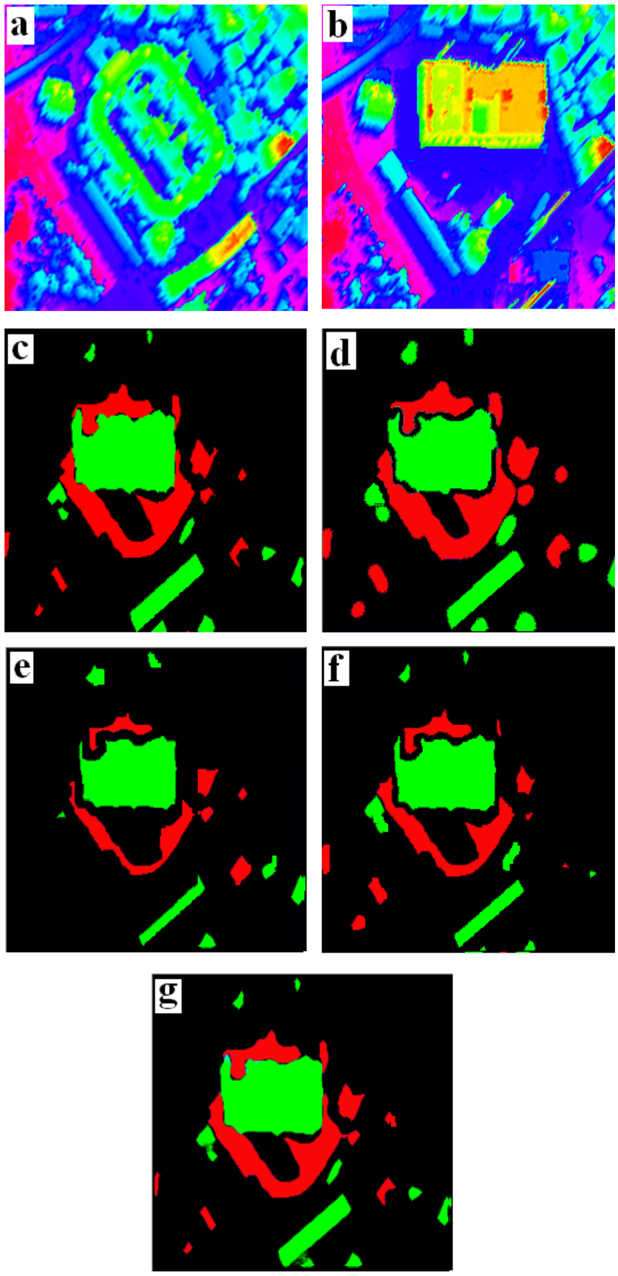

Figure 4. Typical example of the change detection results. (a) is the earlier DEM, (b) is the later DEM, (c) shows the manually digitized reference changes, (d) shows the detected changes by image differencing, (e) shows the detected changes by Principal Components Analysis, (f) shows the detected changes by post-classification based on SVMs, (g) shows the detected changes after applying the Simple Majority Vote. Areas in red are classified as decrease; areas in green are classified as increase; while areas in black refer to both background and unchanged.

The overall detection accuracies of individual techniques, based on the reference data, are given in Table 1. PCA performed the best with 90.2% detection accuracy, followed by Image Differencing and post-classification with detection accuracies of 88.3% and 84.7% respectively.

Method	Detection accuracy (%)
Image Differencing	88.3
PCA	90.2
post-classification	84.7
Simple Majority Vote	96.4

Table 1. Performance evaluation of single detection techniques.

The improvement in detection accuracies achieved by the combination method compared with the best individual detection technique, PCA, was determined as shown in Table1. It is clear that the performances of Simple Majority Vote are better than those of single detection methods. The improvement in detection accuracy of 6.2% is obtained from Simple Majority Vote algorithm.

For the per-region based evaluation, a region was counted as a true positive if at least 90% of its area from the automatically detected results was overlapped with the corresponding area in the reference data. Figure 5 shows the completeness and correctness against the region size. The completeness and correctness of regions around 30m^2 were around 74% and 78% respectively and these statistics improve as the region size increased. Completeness and correctness were over 90% for all regions larger than 50m^2. The difference between completeness and correctness is a matter of 1–2% except for regions smaller than 50m^2 where the difference is up to 5%. This further confirms the lower reliability of detecting regions smaller than 50m^2. It can therefore be concluded that these tests strongly represent achievable accuracies for detection of changes by the proposed method using lidar data.

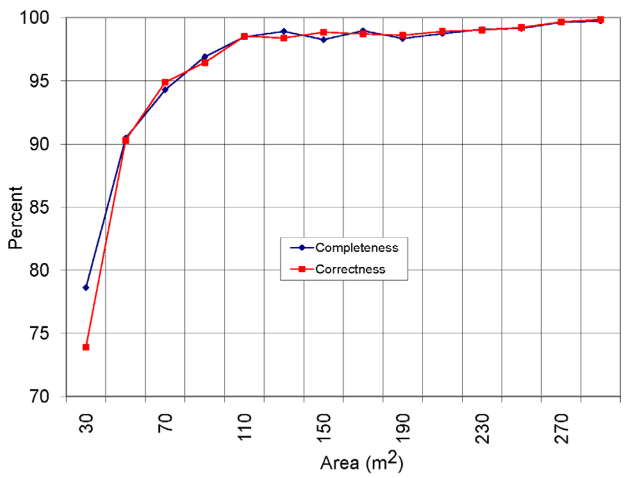

Figure 5. Completeness and correctness derived for the detection process plotted against size of detected areas.

5. CONCLUSION

In this paper, we have applied a powerful method to combine change detection techniques with different performance based on the Simple Majority Vote. To test the algorithm, three change detection methods were based on lidar data of different two epochs. The results showed an improvement in terms of detection accuracy. Detection accuracies of individual algorithms were 84.7%, 88.3% and 90.2% for post-classification, Image Differencing and PCA respectively whereas the proposed fusion algorithm gives an accuracy of 96.4% which is an improvement of around 6.2%**.** On the other hand**,** the proposed method showed a high level of automation and fast computation in change detection process. These results demonstrate the overall advantages of the proposed algorithm for change detection that could be applicable for detecting changes in buildings damaged in a disaster such as earthquake. As a future work, it would be beneficial to use wave-form lidar data instead of discrete lidar point. Spectral information from aerial imagery can also be applied along with lidar data in order to improve the performance of the proposed method, and to refine the results.

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