ROLE OF DIMENSIONALITY REDUCTION IN SEGMENT-BASED CLASSIFICATION OF DAMAGED BUILDING ROOFS IN AIRBORNE LASER SCANNING DATA

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KEY WORDS: Disaster management, Pattern classification, Feature selection, Detection, Complexity, Lidar, Segmentation.

ABSTRACT:

We present a segment-based approach to detecting damaged building roofs in aerial laser scanning data. It consists of a segmentation step, where points are grouped into planar segments, a feature extraction step, and a classification step, where each segment is classified as damaged or intact. Such a segment-based approach faces two major challenges: first, extraction of features that are relevant to the target classes and can adequately distinguish between the intact and damaged segments is not straightforward. Second, the generation of reference segments for training and testing is difficult due the complexity of interpreting point clouds. To overcome these challenges the role of feature selection and dimensionality reduction in training a classifier using few training samples is investigated. We evaluate the performance of several classifiers with different sets of features in terms of classification accuracy. The results indicate the usefulness of dimensionality reduction methods in segment-based classification of aerial laser scanning data with few training samples. With 12 features and 50 training segments a linear classifier outperforms more complex classifiers; however, dimensionality reduction methods result in larger improvements in the performance of complex classifiers.

1. INTRODUCTION

Automated detection of damaged buildings in post-disaster aerial data has become a challenging topic of interest for researchers in the area of mapping and pattern recognition. Existing approaches are mainly based on classification and change detection techniques applied to satellite images (Balz and Liao, 2010; Dell'Acqua and Polli, 2011; Joyce et al., 2009; Kerle, 2010; Korkmaz and Kutay, 2010; Pan and Tang, 2010; Pesaresi et al., 2007), aerial images (Gerke, 2011; Gerke and Kerle, 2011; Guo et al., 2009; Kerle et al., 2005; Turker and San, 2004), and more recently laser scanning data (Oude Elberink et al., 2011; Rehor et al., 2008; Shen et al., 2010; Vögtle and Steinle, 2004). Aerial laser scanning data are particularly suitable for extracting objects of simple geometry such as planar roof surfaces (Khoshelham et al., 2005; Khoshelham et al., 2010; Sande et al., 2010; Vosselman et al., 2004).

In this paper, we investigate a segment-based approach to detecting damaged building roofs in aerial laser scanning data. It consists of a segmentation step, where the points are grouped into planar segments, a feature extraction step, and a classification step, where each segment is classified as damaged or intact. Such a segment-based approach faces two major challenges: first, extraction of features that are relevant to the target classes and can adequately distinguish between the intact and damaged segments is not straightforward. Second, the generation of reference segments for training and testing is difficult. The latter is because of the complexity of interpreting point clouds due to the absence of photometric information. Figure 1 shows an example of an intact and a damaged building captured in an aerial image and laser range data after the earthquake of 2010 in Haiti. For a human supervisor the interpretation of data and making distinction between the intact and the damaged roof is much easier in the image than in the point cloud. On the contrary, classification algorithms are expected to perform better in the point cloud where height information is available and object geometries are represented more accurately.

In practice, the above challenges lead to a dimensionality problem in the classification. While we tend to include as many features as possible to compensate for our lack of knowledge about relevant features, quite often we do not have sufficient training samples to adequately train a high dimensional classifier, because of the difficulty of collecting reference data. The consequence is a poor performance of the classification algorithm. The objective of this paper is to investigate the role of dimensionality reduction in improving the classification of damaged building roofs. We evaluate feature selection methods as well as methods for mapping features to reduced dimensions, and compare their performances in terms of classification accuracy. We also analyse the effect of classifier complexity on learning the classifier from a few training samples.

The paper proceeds with an overview of segment-based classification of damaged building roofs in Section 2. In Section 3, methods for feature selection and mapping to reduced dimensions are described. Section 4 presents the experimental results of dimensionality reduction and classifier complexity. The paper concludes with some remarks in Section 5.

2. CLASSIFICATION OF DAMAGED ROOFS

The basic assumption in the segment-based detection of damaged roofs is that intact roofs appear in laser data as large planar segments whereas collapsed roofs are characterized by many small segments. The detection thus begins with a segmentation step to group individual points into planar regions. Then, a number of features are extracted for each segment. Finally, a trained classifier is employed to classify the segments into two roof classes of intact and damaged. The following sections describe the above steps.

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A B C

Figure 1. Comparison of aerial image and laser data of a damaged and an intact building. A. Pre-event aerial image; B. Post-event oblique aerial image; C. Post-event aerial laser data.

2.1 Segmentation

To segment the point cloud into planar segments the surface growing method developed by Vosselman et al. (2004) is employed. The surface growing algorithm begins with the selection of a number of seed surfaces in a Hough space by identifying the plane parameters that receive the most votes from the object points. These seed surfaces are then grown to neighbouring points that satisfy a coplanarity criterion. Further details of the surface growing algorithm can be found in Vosselman et al. (2004).

2.2 Feature extraction

Feature extraction is the critical step in the segment-based classification of point clouds. Besides the size of the segments which is assumed to be a characteristic feature of intact and collapsed roofs, the relevance of other features to the roof classes is not a priori known. We hypothesize that information about the direction of the plane normal, reflectance, height above the terrain and planarity of a segment (also points that are left out of a segment in the segmentation algorithm, here called unsegmented points), are relevant in distinguishing intact and collapsed roofs. This is realized by extracting 12 features as listed in Table 1.

feat. id	Description
1	number of points per segment (nP)
2	root mean square of plane fitting residuals (rmsRes)
3	ratio of plane fitting outliers (rOut)
4	plane slope (s)
5	z component of plane normal (n_z)
6	mean reflectance per segment (meanRfl)
7	standard deviation of reflectance per segment (stdRfl)
8	minimum height above DTM (minH)
9	maximum height above DTM (maxH)
10	mean height above DTM (meanH)
11	ratio of points in a segment that have an unsegmented point in a neighbourhood of 1 m (rUnseg)
12	mean point density in the bounding box of the segment (meanDns)

Table 1. Features extracted for each planar segment.

2.3 Classification

In statistical pattern recognition the task of classification is mainly to find a discriminant function between the features pertaining to different classes. Such a discriminant function is learned from a number of training samples, i.e. feature vectors with known labels. The performance of a classifier is influenced by the number of training samples, number of features and the complexity of the classifier (Jain et al., 2000).

To analyse the effect of classifier complexity we experiment with three classifiers of different complexity, namely: Bayesian Linear Discriminant Classifier (LDC), Bayesian Quadratic Discriminant Classifier (QDC) and Nearest Neighbour Classifier (1-NN). For a two-class problem the linear discriminant function is defined as (Duda et al., 2001):

$$D_{ldc} = (\mu_1 - \mu_2)^{\mathrm{T}} \Sigma^{-1} x + c \qquad (1)$$

where μ_1 and μ_2 are the mean vectors of the features pertaining to the two classes respectively, $\sum$ is the covariance matrix of the features assumed equal for the two classes, x is a feature vector to which we want to assign a class label, and c is a constant. The quadratic discriminant function is defined as:

$$D_{qdc} = -\frac{1}{2}(x-\mu_1)^{\mathrm{T}} \Sigma_1^{-1} (x-\mu_1) + \frac{1}{2}(x-\mu_2)^{\mathrm{T}} \Sigma_2^{-1} (x-\mu_2) + c \qquad (2)$$

where $\sum_1$ and $\sum_2$ the covariance matrices of the features pertaining to the two classes are assumed to be different.

The nearest neighbour classifier assigns to a test sample the class label of its nearest neighbour in the training set. It has a nonparametric discriminant function, which can take any complex form. Figure 2 shows examples of LDC, QDC and 1-NN for a subset of Iris dataset with 2D features and two classes.

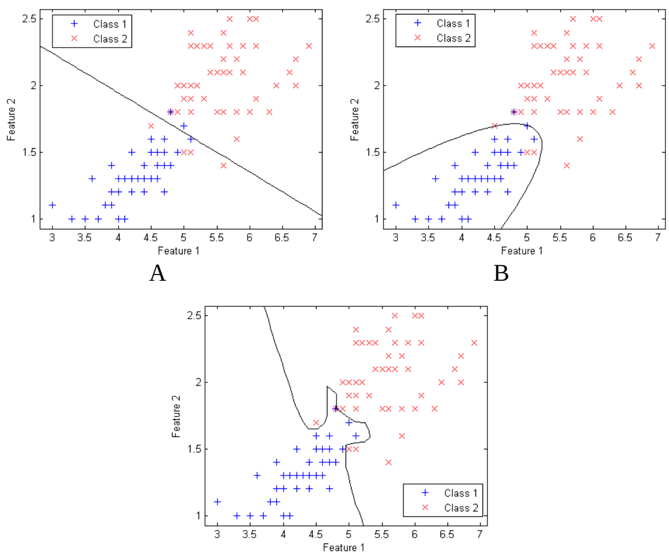

Figure 2. Examples of classifiers in the order of increasing complexity. A: linear discriminant classifier; B. quadratic discriminant classifier; C. nearest neighbour classifier.

3. DIMENSIONALITY REDUCTION

With large numbers of features one would need a large number of training samples to adequately train a classifier. When few training samples are available, the problem of insufficient training can be avoided by reducing the dimensionality of the feature space. Dimensionality reduction can be done either by selecting a subset of features that lead to comparable or even improved classification accuracies, or by mapping the high-dimensional feature space to lower dimensions. The following sections describe these methods.

3.1 Feature selection

Feature selection is essentially a search for a subset of all features that produces the lowest classification error. Several feature search and selection methods exist in literature. In this paper we experiment with the following feature search and selection methods:

- Forward Selection (FS): the search begins with an empty set; then in subsequent steps one feature, whose addition reduces the classification error the most, is added at a time until no further reduction of error is achieved.
- Backward Elimination (BE): the search begins with a full set; then in subsequent steps one feature, whose removal reduces the classification error the most, is eliminated at a time until no further reduction of error is achieved.
- Plus-*l*-take-away-*r* (+*l*-*r*): the search begins with an initial set; then in subsequent steps *l* best features are added according to the FS criterion, and *r* worst features are removed according to the BE criterion.
- Branch and Bound (BB): the full set is sequentially split into smaller subsets; then those subsets that have no part of the optimal subset are eliminated by backtracking.

More detailed description of the feature selection methods can be found in (Jain and Zongker, 1997).

3.2 Mapping features to reduced dimensions

Two common mappings for reducing the feature space dimensions are: principal component analysis and linear discriminant analysis.

Principal Component Analysis (PCA): The PCA mapping seeks a linear transformation of features to a basis defined by the eigenvectors corresponding to the largest eigenvalues of the covariance matrix of features. It is defined as: Y = X·H, where X contains the input features, Y contains the mapped features and H is the transformation matrix whose columns are the eigenvectors of the covariance matrix of X. If all the eigenvectors are used in H, then Y will have the same dimension as X, but if H is constructed out of a few eigenvectors corresponding to the largest eigenvalues then Y will be lower-dimensional than X.

Linear Discriminant Analysis (LDA): The LDA mapping transforms the data to a lower-dimensional space, which maximizes the ratio of between-class scatter to within-class scatter. For a two-class problem the mapping becomes projection to a line: **y** = X·**w**, where X contains the input d-dimensional features, **y** contains the mapped 1-dimensional features and **w** is the mapping. The LDA seeks a mapping that maximizes Fisher's measure of separation between the two classes (Duda et al., 2001):

$$J(\mathbf{w}) = \frac{|\tilde{\mu}_1 - \tilde{\mu}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} \quad (3)$$

where $\tilde{\mu}_1$ and $\tilde{\mu}_2$ are means of the projected features pertaining to the two classes respectively, and $\tilde{s}_1$ and $\tilde{s}_2$ are the corresponding scatters (proportional to variances).

4. EXPERIMENTS AND RESULTS

The laser scanning dataset used for the experiments was acquired over Haiti's capital Port-au-Prince after it was hit by the earthquake of 12 January 2010. Figure 3 shows a visualization of the dataset by colour coding. The dataset has an average point spacing of 3 points per m^2, and contains reflectance data in addition to elevation.

A total of 698 segments were labelled to serve as reference data. The labelling was done by delineating regions in post-event overlapping aerial images and transforming the pixels to the ground coordinate system by forward intersection. Then, the labels were passed from every image-based 3D point to the nearest laser point if the distance between the two points did not exceed a threshold. A value of 1.0 m for the threshold was experimentally found appropriate, corresponding to the relative accuracy of the image-based 3D points and the laser points. Finally, a label was assigned to each segment in the segmented laser data if at least 90% of the points within the segment had the same label.

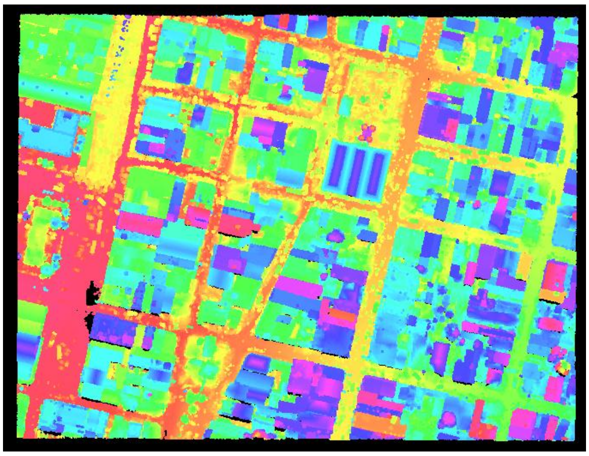

Figure 3. Aerial laser scanning data of the study area.

Experiments with the classifiers and dimensionality reduction methods were carried out using the PRTools Matlab toolbox (Duin et al., 2007). To examine the problem of dimensionality an initial classification of the segments was carried out with different numbers of features and training samples. Figure 4 illustrates the results. Here the features are sorted according to their Fisher distance, and the quadratic discriminant classifier is used. It can be seen that when sufficient training samples are available the weaker features (7~12) do not contribute to the accuracy of the classifier, and when fewer training samples are used the weaker features actually deteriorate the classifier's performance. Figure 5 shows the learning curve of the quadratic classifier with all features. With around 100 training samples the classification errors calculated on the training samples and test samples are close; whereas with fewer training samples there is a large difference between the training error and the test error indicating that the classifier is not sufficiently trained.

This suggests that QDC needs a minimum of about 100 training samples to be sufficiently trained when all features are used.

To test the effect of dimensionality reduction methods on the performance of the classifiers trained with a low number of training samples the following evaluation strategy was used. From the reference dataset 10 sets of training and test samples were generated. Each set was generated by randomly selecting 50 training samples from the reference dataset, and placing the rest of the samples in the test set. This resulted in 10 sets, each containing 50 training samples and 648 test samples. For the evaluation of a given feature set, the classifier was trained by each training set, and the classification error (defined as the ratio of wrongly classified samples to the total number of samples) was estimated using the corresponding test set. The average error and standard deviation over the 10 experiments were then used for the evaluation of the classifier and feature set.

Figure 6 shows the performance of the classifiers with PCA as the dimensionality reduction method. In all three classifiers only the first four principal components seem to be useful for classification. The remaining 8 components do not contribute to the accuracy of the classifiers; in fact, they worsen the performance of QDC. Also, note that LDC outperforms the more complex classifiers regardless of how many principal components are used.

Table 2 summarizes the feature selection results. Note that an optimal subset of features could not be found by all search methods, although it is clear that some features, notably 1 (number of points per segment), 3 (ratio of plane fitting outliers), 10 (mean height above DTM) and 11 (ratio of points located near an unsegmented point), are selected by more search methods. Figure 7 shows the performance of classifiers with different feature selection methods. While the results of different feature selection methods are quite comparable, the simplest classifier, LDC, again performs better than the more complex classifiers with most of the selected feature subsets.

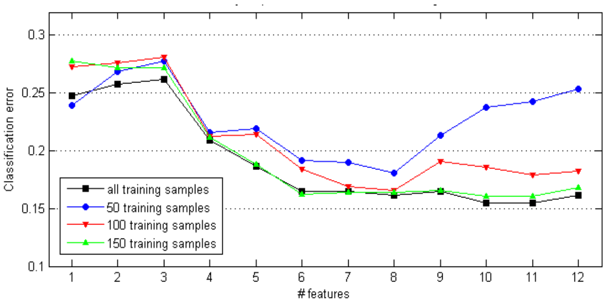

Figure 4. Performance of Bayesian quadratic classifier with different numbers of features and training samples.

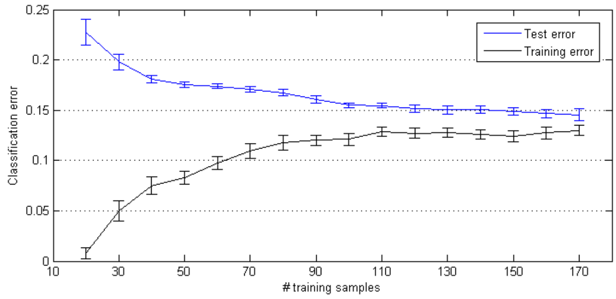

Figure 5. Learning curve of Bayesian quadratic classifier with increasing number of training samples.

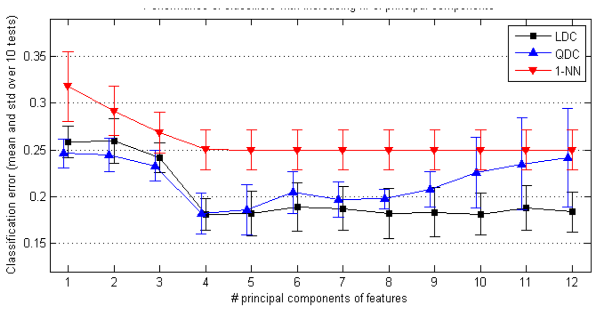

Figure 6. Performance of classifiers with increasing number of principal components of features.

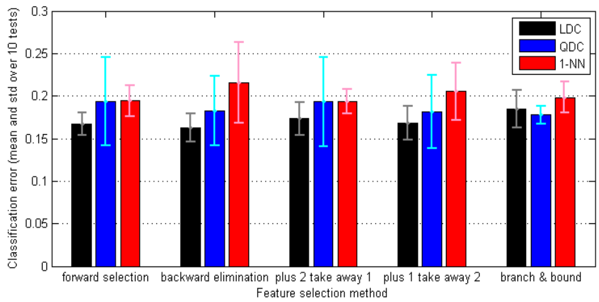

Figure 7. Performance of classifiers with different features selection methods.

Search method	Classifer	Error	Features											
			1	2	3	4	5	6	7	8	9	10	11	12
FS	LDC	0.167	X									X	X	X
	QDC	0.194	X	X	X	X	X	X	X			X	X	
	1-NN	0.195		X	X	X	X					X	X	
BE	**LDC**	**0.163**	**X**		**X**	**X**			**X**	**X**		**X**	**X**	
	QDC	0.183	X	X	X		X		X			X	X	
	1-NN	0.216		X	X					X		X		X
+2-1	LDC	0.173	X		X	X	X		X	X	X	X	X	
	QDC	0.193	X	X	X	X	X	X	X	X			X	
	1-NN	0.194		X		X						X	X	
+1-2	LDC	0.168	X		X		X		X		X	X	X	
	QDC	0.181	X	X	X		X		X	X			X	
	1-NN	0.206		X	X					X	X	X	X	
BB	LDC	0.185	X									X		
	QDC	0.178										X	X	
	1-NN	0.198									X	X		

Table 2. Results of different feature selection methods.

Figure 8 shows a comparison of classification results with different dimensionality reduction methods, including the feature mapping by linear discriminant analysis. In all cases the least complex linear discriminant classifier gives better classification results. The combination of feature selection by backward elimination with LDC leads to the highest classification accuracy of 84%. The classification errors are the largest for the 1-NN classifier. The quadratic classifier performs relatively poorly when all features are used, but its performance improves with LDA and PCA mapping as well as feature selection. In general, classification results of more complex classifiers are more improved by the feature mapping and selection methods.

Figure 9 shows the classification results of LDC with features selected by backward elimination superimposed on an oblique aerial image of the study area. Note that the classified segments are only those which were in our reference dataset. They are somewhat dispersed because of the criteria used for assigning labels to the segments as described in the beginning of this section. In the close-ups of Figure 9 we can see that the method performs well in classifying intact roof segments from those that are completely collapsed into rubble. Most of the classification errors occur in large roof segments that are partly damaged. These are classified as intact while in the reference data they were identified as damaged roofs.

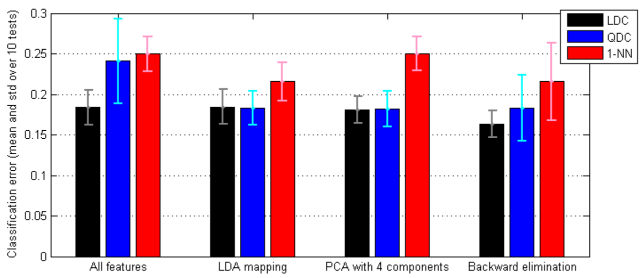

Figure 8. Comparison of dimensionality reduction methods.

5. CONCLUSIONS

In this paper we investigated the problem of dimensionality in segment-based classification of damaged roofs in aerial laser scanning data. It was shown that presenting a classifier with many features but not enough training samples will result in poor classification results. When such a situation is unavoidable, feature selection methods as well as methods for mapping features to reduced dimensions in general lead to an improved performance of the classifier. Our experimental results also showed that less complex classifiers perform better when the number of training samples in proportion to the number of features is small.

In this study we considered only two classes of intact and damaged to classify the roof segments. In reality, many roof segments are only partly damaged while many others are totally collapsed into rubble piles. Extending the segment-based classification method with more classes to obtain better classification results will be a topic of future research.

ACKNOWLEDGEMENTS

The authors are grateful to Markus Gerke for helping with the generation of the reference data. We also thank Pictometry Inc. for providing the imagery used in this study. The aerial laser scanning data were acquired by Rochester Institute of Technology and Kucera International, under sub-contract to ImageCat Inc. and funded by the Global Facility for Disaster Reduction and Recovery (GFDRR) hosted at The World Bank.

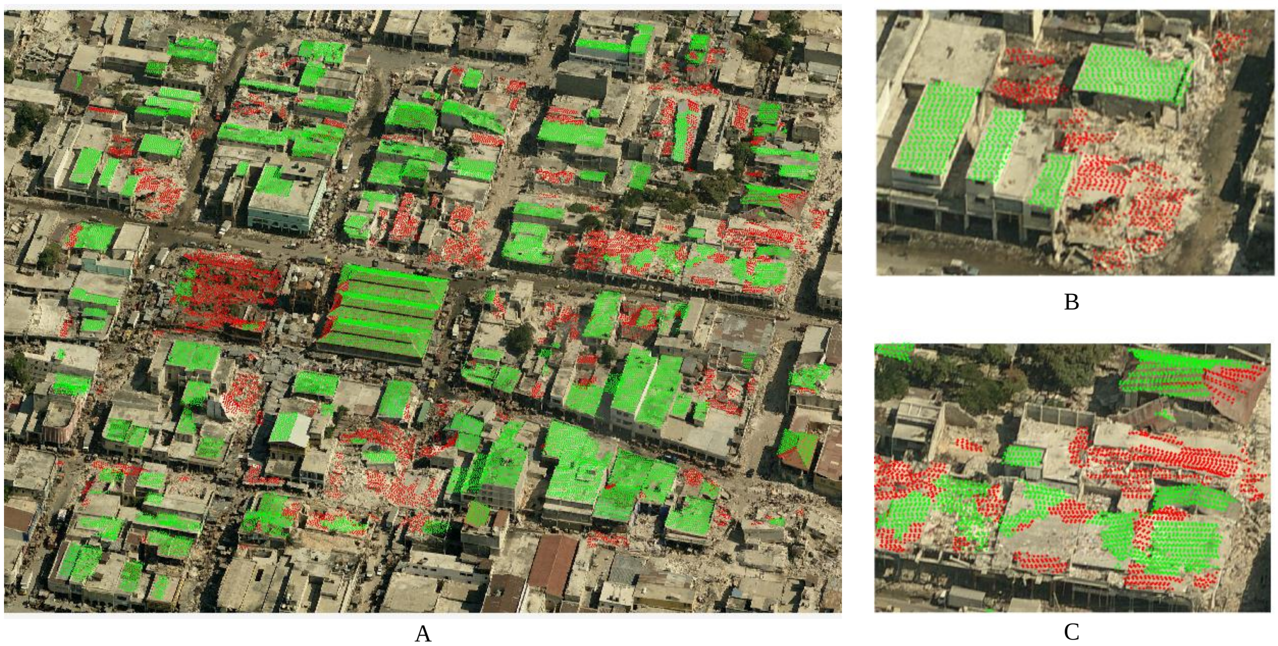

Figure 9. Classification results. A. laser segments classified as intact (green) and damaged (red) superimposed on an aerial image of the study area; B. close-up of some correctly classified segments; C. close-up of some wrongly classified segments.

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