Concrete Damage Detection based on Machine Learning Classification of Terrestrial Laser Scanner Point Clouds

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Key words: TLS, Damage assessment, robust PCA, Supervised classification, SVM

SUMMARY

The detection of surface damage on concrete structures is an important requirement to assess the integrity and safety of the structure. This paper develops a machine learning-based model for high-precision detection of damage on concrete surfaces using terrestrial laser scanner point clouds (PCs). The developed damage detection model relies on a support vector machine (SVM) algorithm to train a point-wise defect classifier for locating the concrete damage. It employs an unsupervised defect clustering approach to accurately annotate the training data without the need for exhaustive manual interventions. The distinctive features used in this classifier include local point density and a variety of eigenvalue-based features such as change of curvature, eigenentropy, and dimensionality features. The statistical redundancy and correlation of features are assessed through a classifier-independent statistical measure. The influence of the selected features and the model parameters are investigated. The performance of the proposed approach was evaluated extensively on three real datasets: a 12 m long span comprising the first five flumes of a concrete aqueduct with over 250 million points as well as two civil pedestrian concrete structures with 150 million points and 10 million points, respectively. A small part of the aqueduct site with 9000 points on concrete surfaces, balanced between points with and without damage, was used for training the system. The use of machine learning with a relatively heterogeneous dataset enables the development of a concrete damage detection system that can account for limiting conditions of PC processing, e.g., irregular and varying point density and optimal neighbourhood size, and enables detection of various types of concrete damage. The results obtained from these three datasets demonstrate the validity of the proposed supervised model for reliable prediction of the location of damage of any type which makes roughness as small as 1 cm or smaller on the surface of concrete structures captured with any laser-scanning PC with a minimum spatial resolution of 5 mm. This yields an average classification precision and F1-score of 97.33% showing the potential of using machine learning for concrete damage detection.

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1. INTRODUCTION

Concrete infrastructure is subject to damage and deterioration through years of functioning under the influence of natural events and human activities. Early detection of a damaged concrete surface allows timely maintenance procedures to counter the side effects that derive from them and leads to a longer lifetime for the structure (Mehta and Monteiro, 2006). Traditional diagnostic methods of concrete damage assessment are rather time consuming and difficult in terms of safety. Remote sensors have offered high spatial resolution and overcome the limitations associated with the traditional inspections and provided reliable and efficient visual inspections especially for hard-to-reach areas in large structures. Terrestrial laser scanner (TLS) technology can cover a full 360°×310° panoramic view in each single acquisition and directly generates dense 3D PCs within few minutes with a high precision and resolution (Walton et al., 2014). In the past few years, much research has used TLS PCs for structural health monitoring, e.g., Valença et al. (2017) used geometric information captured by TLS to compensate for drawbacks of image orthorectification in image processing crack detection methods. Hadavandsiri et al. (2019) detected concrete surface damage solely using spatial TLS PC coordinates. For furthre review of the traditional concrete inspections and Image-based damage detection techniques the readers are referred to Hadavandsiri et al. (2019).

PC processing methods can detect damage on the surface of a structure based on the surface roughness and local orientation of points with respect to a reference surface simulating the intact condition of the structure (Liu et al., 2011). In this regard, points are classified as either damaged or undamaged. Feature descriptors within the local neighbourhood of each point provide insight into the structural geometric condition and are thus used to classify the points (Dittrich et al., 2017). Although damage assessment based on image classification is an extensively researched topic, to the best of the authors' knowledge, using spatial PCs for damage classification is still in its infancy. Most PC damage detection methods rely on unsupervised classification schemes which represent a challenging task due to the following limitations: (1) detecting specific shapes of defects occurring on specific geometric surfaces such as flat planar structural components (Kim et al., 2014); (2) high dependency on appropriate threshold values (Mizoguchi et al., 2013) which are inconsistent and change for different datasets captured in different environments; (3) lack of robust statistical methods to suppress data artefacts while maintaining information about surface flatness (Chen et al., 2018). In addition, the unsupervised classification approaches are not capable to account for all geometric features describing the structural geometric condition of PCs captured from concrete surfaces.

In the past few years, machine learning and deep learning techniques, convolutional neural networks (CNN) in particular, have significantly outperformed other image classification techniques. Nevertheless, there has been considerably less research on adapting the learning algorithms for the classification of PCs having a more complex and irregular 3D structure than images. For supervised classification of PCs, schemes based on AdaBoost (Lodha et al., 2007), Gaussian Mixture Models (Lalonde et al., 2006), Random Forests (Chehata et al., 2009) or Support Vector Machines (SVM; Wurm et al., 2014) have been proposed in the literature. With this vision in mind, this paper focuses on developing a new paradigm for supervised damage classification solely using the spatial TLS PC coordinates. The developed system is a multi-label classifier that will predict each point class as damage, planar (non-damage) or outlier. The obtained results provide insight to machine learning-based algorithms for damage detection. The proposed methodology for a supervised damage classification approach is explained in the following sections. Section 2 introduces the algorithm, followed by a brief explanation of the basics necessary for implementing the applied SVM. Section 3 describes the data training. Section 4 describes feature selection. The performance of our framework is illustrated by the conducted experiments and the respective results in Section 5. Finally, conclusions and open problems are presented in Section 6.

2. SUPERVISED CLASSIFICATION

Supervised classification schemes exploit a training dataset in order to train a classifier that is then used to predict the classes of new (unseen) data. The training data is provided by an assignment between a feature vector in a d-dimensional feature space and a respective class label. The test data only containing feature vectors in the d-dimensional feature space are to be classified. This work formulates the detection of damage as an SVM classification problem that uses a variety of features to train a classifier for predicting whether a measured point on the concrete surface corresponds to damage, non-damage or outlier.

2.1 Feature extraction

In the proposed algorithm, a variety of geometric features including measured range, incidence angle, verticality (Demantké et al., 2012), local point density and a variety of eigenvalue-based features derived from the 3D structure tensor was extracted to characterize the local neighborhood of each 3D point. The derived features all have different scales and thus each feature is normalized to the interval [0, 1]. As illustrated in Hadavandsiri et al. (2019), a minimum density of 5 mm point spacing and a fixed neighbourhood range search of 2.5 cm is required for detecting small damage of 1 cm. Whereas for slightly rough damage smaller than 1 cm, a smaller neighbourhood size of 1 cm and density higher than 5 mm point spacing is required for more accurate detection. For this reason, the training examples contained various points at both 5 mm point spacing and denser. For each single point the features mentioned above are then extracted by the spatial relationships to its 2.5 cm and 1 cm neighbors. The local point density, represented by the K number of points encapsulated in the fixed range search neighbourhood, is used in the SVM model. In this context, a variety of density-representative features can be extracted and used as discriminative damage descriptors. This is the fact that both outlier and damage points exhibit roughness which can be measured by the residual values i.e., distance of the quary point from the plane fitted at its neighbourhood. If the residual distance is larger than a thereshold (e.g. the minimum eigenvalue) the point is counted as out-of-plane; otherwise it is a planar point. The residual distance can be positive or negative depending on the direction in which the point is deviated from the plane. The counted number of points considered as either planar/out of plane/ negative/ positve, as illustared in Fig 1, is divided by the total number of encapsulated points in each neighbourhood, K, which yields the respective density features for each point.

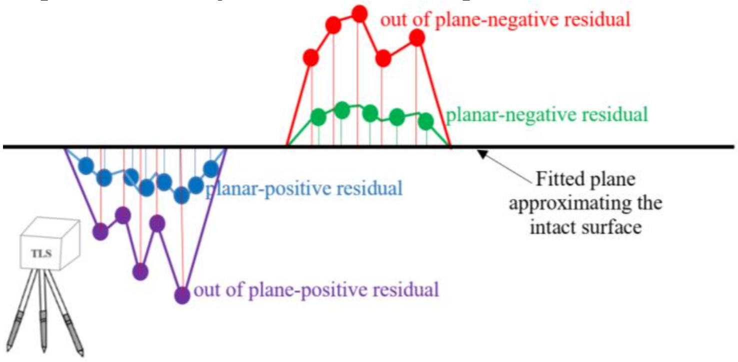


Fig 1. Schematic illustration of point counts representing local point density.

2.2 SVM

SVM is a kernel-based machine learning method for classification, regression, and other learning tasks. The SVM learns a hyperplane or a set of hyperplanes in a feature space to linearly separate two classes of data points so that the margin between training points and the plane is maximized. Often a linear separation in the feature space is not possible, thus, the so-called kernel trick is applied. To separate nonlinear classes, first a kernel function implicitly maps the data into a higher dimensional feature space. A separating hyperplane is then constructed in this feature space where the data is linearly separable. The hyperplane is constructed by solving a quadratic problem (Alpaydin, 2014). A parameter commonly denoted as C or the soft margin is used to penalize the occasional mislabeled training points and adjust the trade-off between maximizing the margin and minimizing the training error. In this work, the Gaussian radial basis function (RBF) is used as the kernel function. Since SVM is a binary classifier, here, the multi-class classification is solved by combining several binary SVMs as provided in the LIBSVM package (Chang and Lin, 2011) and this is done based on a one-against- one approach. The classification results are strongly affected by hyper-parameters–parameters that are not directly learned within the estimator–including: (1) the parameter C penalizing classification errors; and (2) the parameter γ representing the length-scale parameter of RBF kernel. A five-fold cross-validation based on a grid-search in a suitable subspace (C, γ) is applied in order to optimally select these hyper-parameters. To do so, the training set is divided into two disjoint sets T_1 (new training set) and T_2 (validation set). Subsequently, at each point on the discrete grid, the performance of the classifier is evaluated by training on T_1 with the current parameter choices and testing on the T_2. Resulting from this, those values (C, γ) are selected which yield the best performance. Throughout all this work the implementation of LibSVM provided by the scikit-learn Python library is used.

2.3 Model evaluation

The classification model performance will be explained by four model evaluation metrics commonly used for classification: (1) precision, (2) recall (3) F_1-score which combines precision and recall with equal weights, and (4) accuracy. This is expected that feature selection and hyper-parameters tuning improve the model evaluation metrics.

3. TRAINING DATA FROM UNSUPERVISED DAMAGE CLASSIFICATION

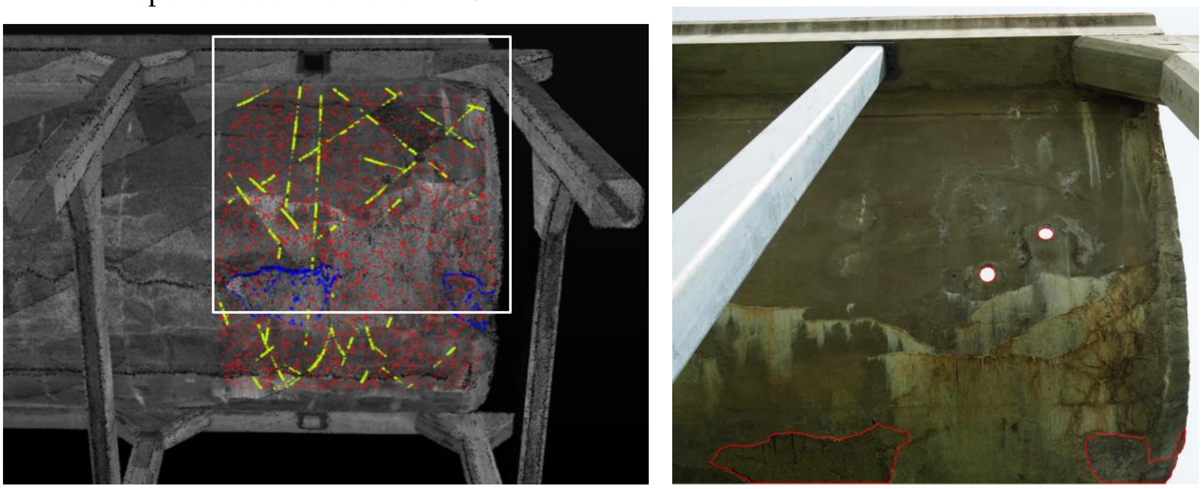
The unsupervised damage classification proposed in a previous publication of the authors (Hadavandsiri et al., 2019) is used to accurately annotate the training data and thus avoid the cumbersome work of manually labeling training points. Hadavandsiri et al. (2019) assessed the impact of point density, neighbourhood size, damage size and data artefacts on damage detection and developed an unsupervised point-wise defect classifier. The classifier was capable of locating damage of any type exhibiting roughness as small as 1 cm or smaller on the surface of concrete structures captured with any laser-scanning PC with a minimum spatial resolution of 5 mm. In their unsupervised method, local surface variation (LSV) or change of curvature, which is a highly defect-sensitive feature, is calculated for each point. Although high LSV potentially represents surface damage, it can also be the result of outliers present in the laser scanning PCs. Therefore, a robust version of principal component analysis (robust PCA) is applied to distinguish between actual structural damage and outliers. Afterwards, the derived robust LSV feature is examined against a systematically defined threshold to determine whether the point should be labelled as damage. Consequently, each 3D point is automatically assigned a label indicating whether it is damage or non-damage and query points removed as outliers are classified as outliers. The results of unsupervised labelling are manually verified to ensure the removal of false-positive labels, and then they are used to train the SVM classifier. This classifier can consequently be used to predict the location of damaged points. Unlike the unsupervised classifier used for labelling the training data, a more extensive variety of descriptive features, extracted from the local neighbourhood of each point, contribute to the SVM classification. This supervised approach is also computationally more efficient than the unsupervised method based on robust PCA and is, thus, applicable to large PCs.

The first dataset captured from the surface of a concrete heritage aqueduct (Hadavandsiri et al., 2019) was used to train the model. Since the prediction model mirrors the knowledge used during its training, a training dataset sufficiently representative of damaged concrete surfaces is the key in the development of an appropriate tool. Hence, the main idea was to select the train examples from small pieces of the aqueduct at different surface appearance to increase the diversity of the trained dataset and, consequently, of the machine learning system that learns from this dataset. This dataset was divided into a training set and a testing set at an 80/20 ratio. The unsupervised labelling process, mentioned above, assigned each point one of the three semantic labels: damage, non-damage and outlier. At first, the number of selected samples per class varied significantly for both training set and test set. Since an unbalanced distribution of training data per class often has a detrimental effect on the SVM model (Criminisi and Shotton, 2013), we reduce these sets to equal class size so that the sets become balanced between points with and without damage as well as outliers. This is done by randomly sampling the same number of 3000 training examples encapsulated per class. The respective number of samples per class is provided in Table 1.

Table 1. Number of samples per class for the training dataset.

Class	Training set (points)	Test set (points)	Sum(points)
damage	2400	600	3000
non-damage	2400	600	3000
outlier	2400	600	3000
sum	7200	1800	9000

The system was trained with the extensive variety of features derived from these 9000 points selected on the first flume of the south facing side of the western part of the aqueduct as shown in Fig 2. The diversity of the training data as well as the variety of the derived features make the system learn the impact of irregular point density, optimal neighbourhood size, variety of damage size, and outlying points on damage detection. Consequently, the SVM classifier is expected to detect surface damage of any type as small as 1 cm or smaller from PCs with a minimum spatial resolution of 5 mm.



(a) (b)

Fig 2. (a) The 3000 training examples per class; (b) is the corresponding digital image of the rectangle in (a). Throuout this paper, PCs are visualized as damage points in blue, locally-planar points in red and outlying points in yellow. Areas of damage were manually delineated on the imagery in red for validating the relative position of the corresponding defective areas identified from the scans.

4. FEATURE SELECTION

Whereas a large variety of descriptive features can be exploited and contribute to the classification, it has to be considered that the data contains some features that are redundant or irrelevant. They have been demonstrated to adversely affect a classifier performance but can be removed without incurring much loss of information (Guyon and Elisseeff, 2003). Feature selection is the process of selecting a subset of features that are most relevant and informative of the predictive modelling problem e.g., the geometric condition of damaged points. Feature selection reduces model complexity, reduces misleading data improving the modeling performance, reduces overfitting, shortens training times and thus reduces both processing time and memory consumption (James et al., 2013). Feature selection in 3D PC processing has rarely been applied in the literature (Weinmann et al., 2015). Feature selection strategies can be categorized into filter-based methods, wrapper-based methods and embedded methods. Both wrapper-based and embedded methods involve a classifier and thus select feature subsets which are only optimized with respect to the applied classifier. The selected feature subset should be generally applicable for detecting a variety of damage types occurring on any concrete structure. For this reason, it should not depend on the use of a specific machine learning classifier (Weinmann et al., 2013). on the other hand, filter-based results exhibit more generality as they evaluate intrinsic properties of data. Furthermore, filter methods are much faster as they avoid an exhaustive classifier training and tuning. Thus, we focus on filter-based methods and accept that they provide a slightly weaker performance than wrapper and embedded methods.

4.1 Filter-based methods

Filter-based methods are classifier-independent and apply a statistical measure of features' correlation to assign a scoring to each feature in the training data, which results in a subset of the best-ranked features (Weinmann et al., 2015). They are often univariate and consider the feature independently i.e., use only feature-class relations for selecting the best-ranked features with the highest relevance. Whereas multivariate techniques use both feature-class relations and feature-feature relations for selecting features with the minimal redundancy. There is a suite of different statistical measures for classification such as the Chi-squared test, the Fisher test, information gain and Pearson correlation coefficient scores. We used the analysis of variance (ANOVA) statistical test, which is a univariate measure appropriate for classification tasks. It takes two arrays, the features and labels, to assess whether a class label is independent of a particular feature and returns univariate scores for each feature. A feature subset consisting of the best-ranked features are then selected. The influence of the selected features on the performance of the classification model is examined in the following section.

4.2 Impact of feature selection

The features sorted according to their ANOVA relevance rank calculated for the train dataset of 9000 points are demonstrated in Fig 3. We examine different feature sets as cases (1) all features; (2) all features except intensity and verticality; (3) the meaningful subset of 30 best-ranked features, i.e., excluding intensity, verticality, range, incidence angle and scanner to plane distances; (4) only change of curvature. For all examined cases, the (C, γ) hyper-parameters are tuned via cross-validation where training is performed on the feature reduced training set and validation is carried out with the feature reduced validation set. The performance of the SVM classifier is then evaluated on the respective feature reduced test set. The weighted average F1-score for different feature subsets is provided in Table 2. The confusion matrices are depicted in Tables 3 and 4 where the upper row represents the predicted labels and the left column represents the true labels.

A clear trend visible from the feature ranking, quantified in Tables 2 through 4, reveals that the intensity and verticality are the least relevant features and the performance of SVM is improved by removing them. However, range, incidence angle and scanner to plane distance, which are also among the lowest ranked features, can still slightly improve the model performance and thus they were kept in the SVM model. The change of curvature is a strong feature to distinguish between planar structures and non-planar structures representing damage, which agrees with a priori knowledge. However, using more features improves the classification performance, therefore, the proposed supervised classifier outperforms the unsupervised defect clustering used in the training process which only utilizes the change of curvature.

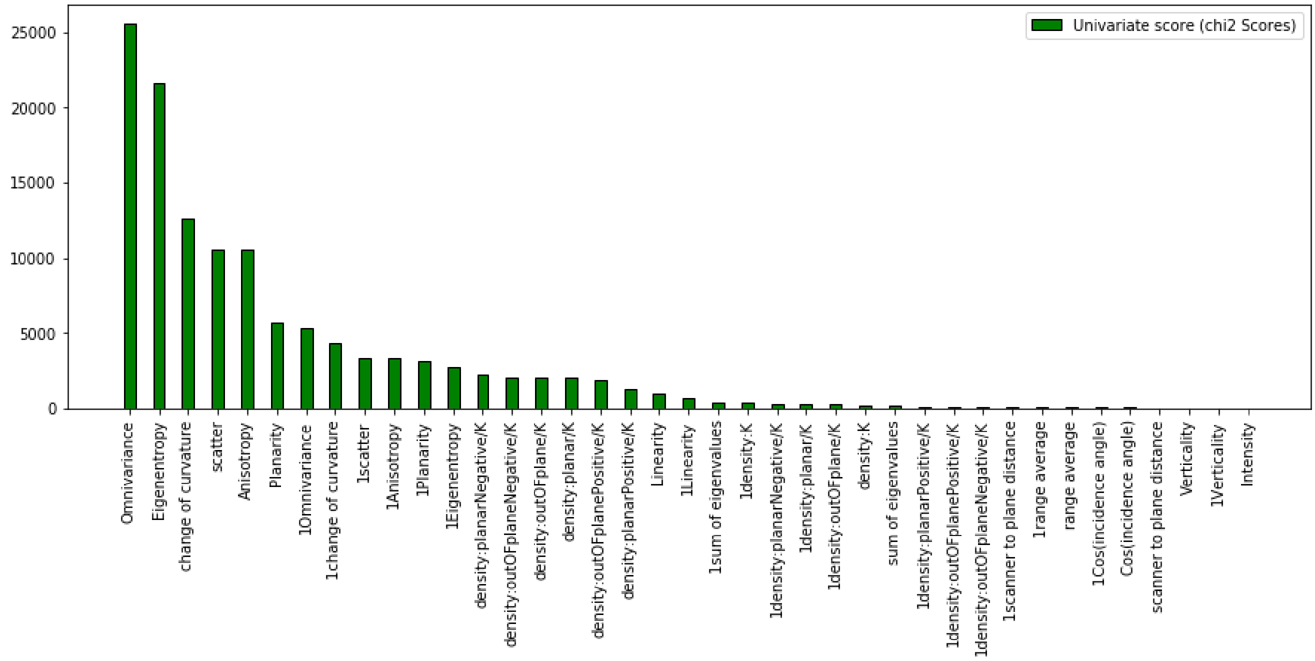


Fig 3. ANOVA rank of the features derived from the 9000 training points; features extracted from 1 cm neighbors are named starting with 1 to be distinguished from features extracted from 2.5 cm neighbors.

Table 2. weighted average multi-class F1-score in % for different feature subsets.

	F1-score
all features	95.80
all features except intesity and verticality	96.38
30 best-ranked features	95.10
change of curvature	86.54

Table 3. Confusion matrix: left for all features, right for all features except intensity and verticality.

	damage	outlier	planar	recall
damage	596	4	0	0.9933
outlier	10	568	22	0.9467
planar	11	16	573	0.9550
precision	0.9660	0.9660	0.9630	

	damage	**outlier**	**planar**	**recall**
damage	**595**	**4**	**1**	**0.9917**
outlier	**4**	**578**	**18**	**0.9633**
planar	**9**	**12**	**579**	**0.9650**
precision	**0.9786**	**0.9731**	**0.9682**	

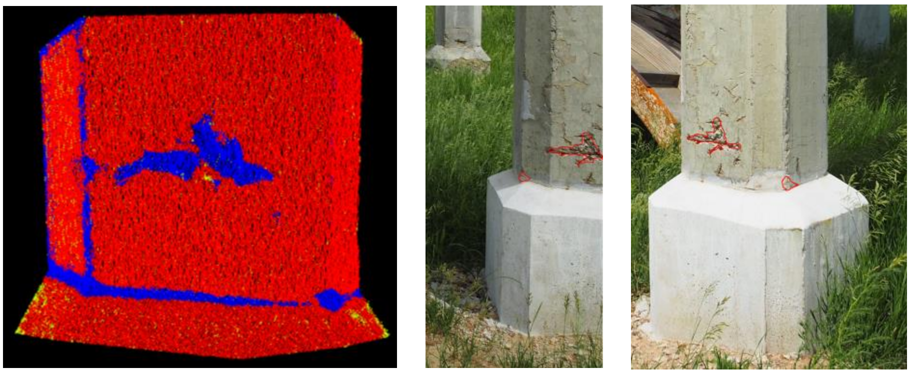
Table 4. Confusion matrix: left for 30 best-ranked features, right for change of curvature.

	damage	outlier	planar	recall
damage	597	3	0	0.9950
outlier	10	556	34	0.9267
planar	14	28	558	0.9300
precision	0.9614	0.9572	0.9426	

	damage	outlier	planar	recall
damage	592	8	0	0.9867
outlier	27	437	136	0.7283
planar	6	33	561	0.9350
precision	0.9472	0.9142	0.8049	

5. EXPERIMENTAL RESULTS

Eventually, the SVM model was tuned and trained based on the subset consisting of all features except intesity and verticality, as it provides the highest model performance (bolded in Table 3, right). Afterwards, the model was used to predict the point classes for unseen PCs: the rest of the aqueduct, the second data set captured of a concrete pedestrian overpass on the University of Calgary campus (Hadavandsiri et al., 2019), and the third data set captured from a concrete entrance to a pedestrian underpass. The visual inspection by the corresponding digital imagery of the classified scans shown in Figs 4 through 10 suggest the success of the developed SVM model for concrete damage detection. As shown in all figures, straight lines along the edges are flagged as blue (damage), however they are not damage. Since our damage detection approach is based on plane fitting, it causes that the object shape (extended planar structures versus edges) has an influence on damage detectability. As a result the edge sections are more probable to be detected as damage. The reason that edge areas are erroneously detected as damage is not only due to the object shape influence mentioned above, but also the fact that the concrete edges are inherently rough due to construction errors. Fortunately, these lines are straight and are thus distinguishable from damage.

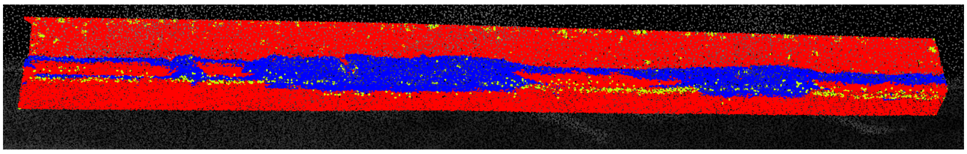


(a) (b) (c)

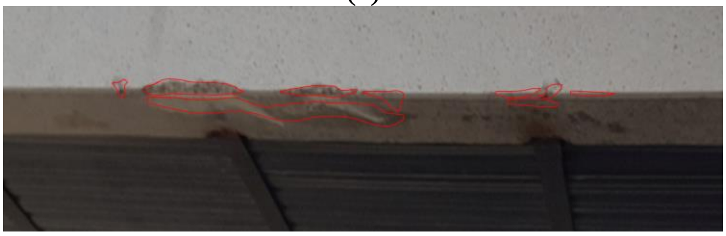
Fig 4. Bottom of the first column of the south facing side of the western part of the aqueduct. (a) multi-class prediction by SVM; (b) and (c) are the corresponding digital images.

(a) (b)

Fig 5. Middle of the first column of the south facing side of the western part of the aqueduct. (a) multi-class prediction by SVM; (b) is the corresponding digital image.

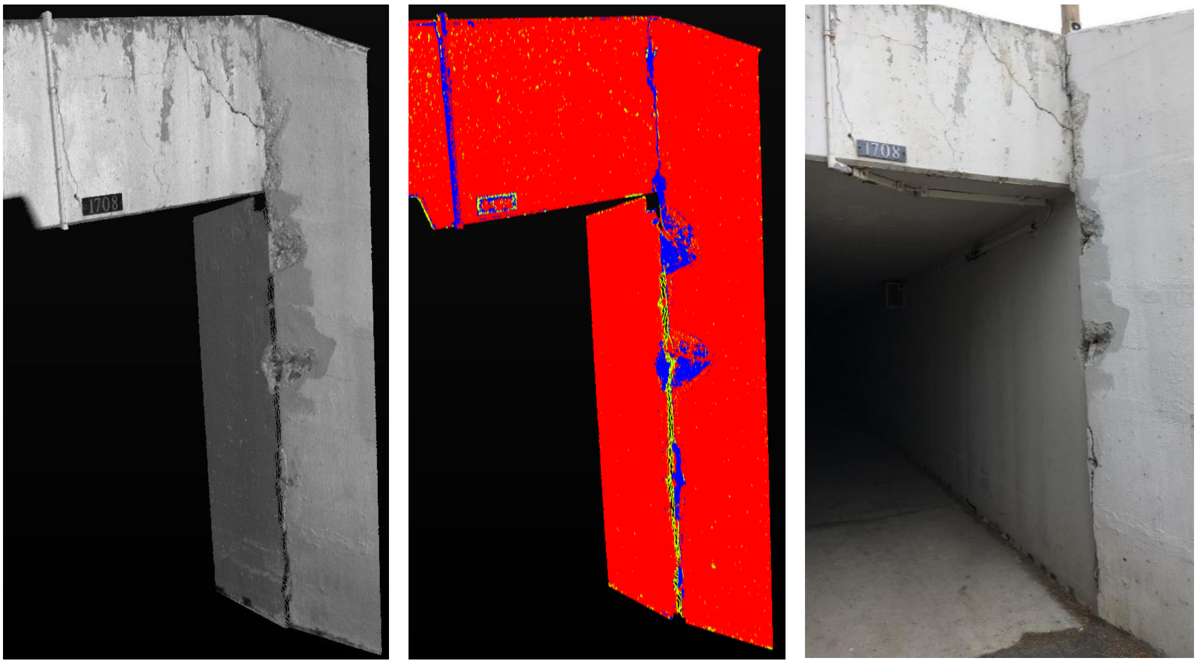


(a)



(b)

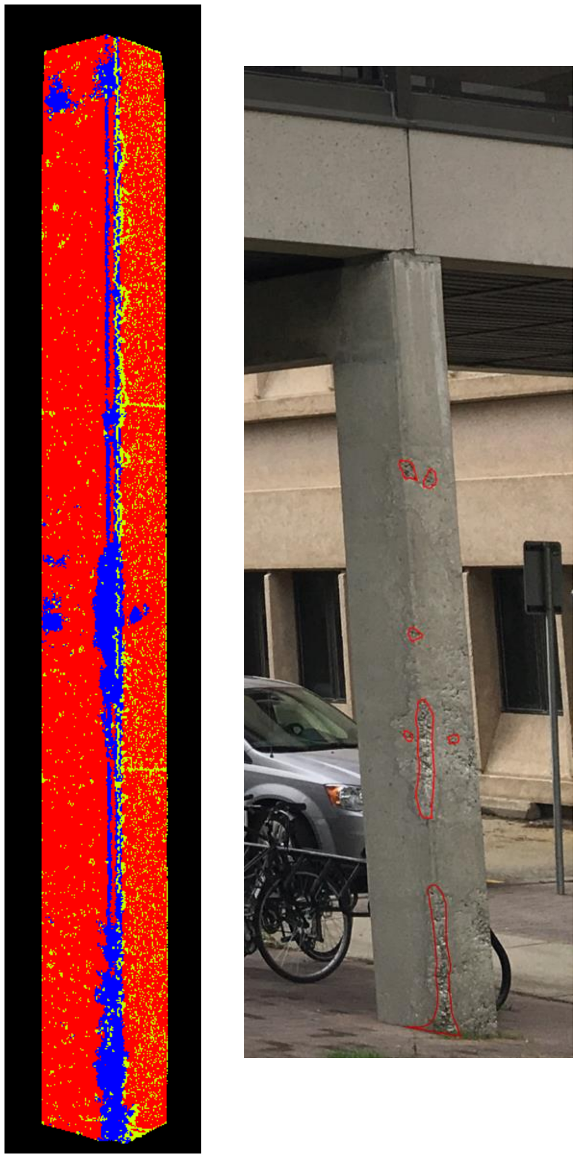
Fig 6. South side of the on-campus pedestrian overpass. (a) multi-class prediction by SVM; (b) is the corresponding digital image.



(a) (b) (c)

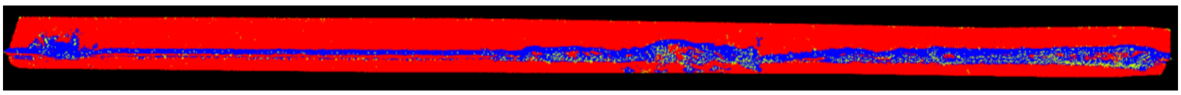
Fig 7. The civil concrete entrance to a pedestrian underpass. (a) the grey intensity PCs; (b) multi-class prediction by SVM; (c) is the corresponding digital image.

In Fig 10, there are many points classified as outliers. This is due to the fact that there are many overlapped scans in this part of the aqueuct and although the scans are well registered but still there are registration errors which are caught as outliers.



(a) (b)

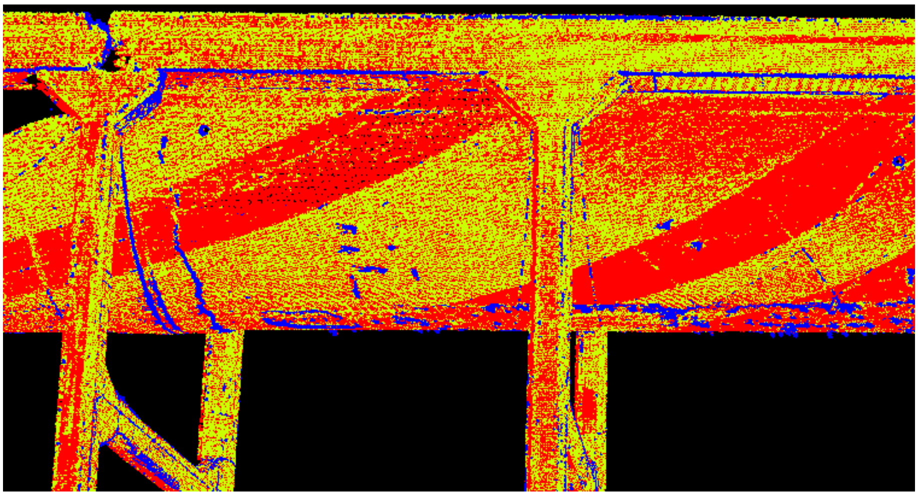
Fig 8. Column on north side of the on-campus pedestrian overpass. (a) multi-class prediction by SVM; (b) is the corresponding digital image.



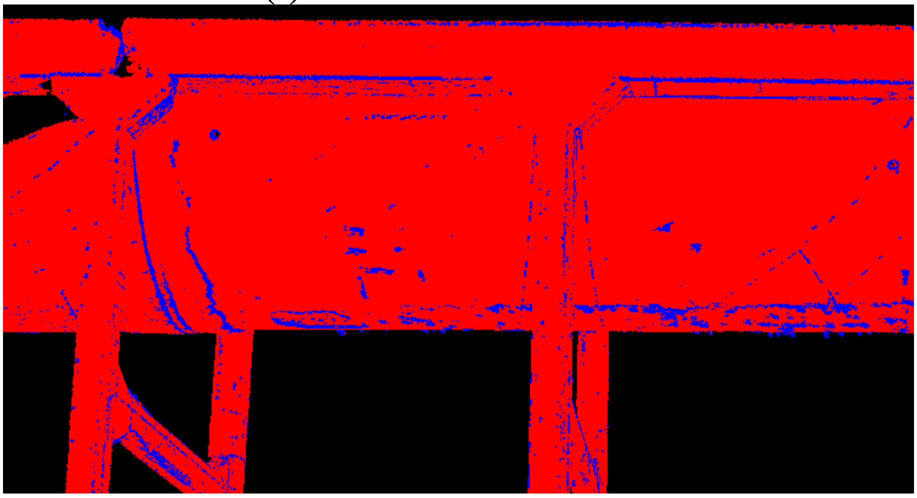
(a)

(b)

Fig 9. North side of the on-campus pedestrian overpass. (a) multi-class prediction by SVM; (b) is the corresponding digital image.



(a)



(b)

(c)

Fig 10. Fourth and fifth flumes of the south facing side of the western part of the aqueduct. (a) multi-class prediction by SVM; (b) the outlier point classes in (a) are turned off; (c) is the corresponding digital image.

The previous unsupervised damage clustering algorithm (Hadavandsiri et al., 2019) needs to be repeated with both 1 cm and 2.5 cm neighbourhood sizes to ensure detecting any damage either smaller or larger than 1 cm. However, in the proposed SVM damage classification model, features derived from both 1 cm or 2.5 cm neighbourhood sizes contribute to predict the class labels and thus the model is able to automatically detect any size and type of damage.

6. CONCLUSIONS AND FUTURE WORK

The implementation of a machine learning-based model for PC damage classification was introduced. The analysis carried out on various real-world PCs proved the suitability of SVM to train the model with a limited dataset size providing a good solution in terms of both model performance and computational efficiency. The model is capable of a point wise detection of any damage type as small as 1 cm or smaller on concrete surfaces captured with any laser-scanning PC at a minimum spatial resolution of 5 mm providing a classification precision close to 100%. Selecting only a subset of the most relevant features to PC damage detection is profitable in terms of model performance, processing time and memory consumption. The fewer features that are used, the less memory and time that is consumed. We avoided the need to label training data manually by using an unsupervised clustering that exploits the surface curvature for labeling sets of example train points. It was demonstrated that the proposed supervised classifier exploiting a variety of features outperforms the unsupervised defect clustering that detects damage only based on the surface curvature. Thus, it is concluded that machine learning-based models are likely to provide faster and more productive inspections for structural damage assessment and health monitoring. For future work, the classification accuracy can be further improved by involving contextual classification techniques that exploit relationships among point labels in a local neighbourhood of each point. The uncertainty associated with the feature measurements is propagated to the classification predictions. Therefore, it is desirable to know the probability for a class label. While the decision function of SVM does not yield class probabilities, other techniques such as logistic regression is suggested to transfer the SVM coefficients toward probabilities in order to yield a damage probability map in the future research.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the Natural Science and Engineering Research Council of Canada (NSERC) for funding this research.

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