On road defects detection and classification

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Abstract. The road pavement condition is affected by various impacts such as trucks, deicing reagents, base erosion, etc. After some time on the road surface occur defects. Engineers are commonly used to collect pavement surface distress data, during periodic road surveys, but it takes a lot of time and manpower. In this paper, we present our automatic defects detection and classification on road pavement method. We suggest the novel approach to detect the different types of defects such as rupture of the road edge, potholes, subsidence depressions. Images of road pavement have been preprocessed to noise filter and smooth, then classified two class - defects/ non defects, next step to process with defects class. We propose three main steps in our approach. First step is to detect defect position (ROI). In the second step, defect is described by its features. The last step is to classify defect each using these different defect features such as Chain Code Histogram, Hu-Moments, size of defect region(width and length, area) and histogram of image. In our approach the following algorithms have been used: Markov Random Fields for image segmentation, Random Forests algorithm for data classification. Data collection on real roads, real-time processing and comparison with other algorithms, analyzes the advantages and disadvantages of each methods.

Keywords: Feature extraction, defect pavement, defects detection, Markov random fields, Graph cut, Random Forests

1 Introduction

For effective management of the road networks, one needs accurate and up to date information about road pavement defects. Thousands of kilometers of road pavement need to be inspected each year. Earlier, road defects information was obtained manually by human inspectors. But such manual methods are very slow and uncomfortable for inspectors and road users. In the last years, several automated inspecting techniques were implemented. Many of these state-of-the-art technologies involve machine vision and machine learning method. The objective of this article is to contribute to this field.

Defect detection problem becomes especially difficult for noisy surfaces.[13] There are many different types of texture can be encountered on the road. In addition, texture depends on current zones of the image due to different regions. Moreover, texture can have big aggregate size. Due to these reasons it can be difficult to distinguish crack and part with extraordinary texture.

Road pavement defects exist in many forms such as: rupture of the road edge, cracks (grid cracking, large crack), potholes, subsidence depressions. Each form of road pavement has got certain features, which are not the same, help us to distinguish them. If we only consider the simple features such as: shape descriptors, region descriptors (length, width, area) the data is unclear and difficult to apply defects road pavement recognition. An image can be considered as a mosaic of different texture regions, and the image features associated with these regions can be used for recognition. The purpose of this paper is to study the use of combination of different types of features, in particular, textural. The article is organized as follows. First we provide brief overview of related work. Then we describe defect pavement detection method and improve quality of image segmentation by Markov random field. Finally, we present data classification based on Random Forest algorithm and conclusions.

2 Related Work

Several researchers have considered the use of such texture features for pattern retrieval [15], [17]. Texture analysis algorithms can use: Markov Random Fields [1] and Random Forests [4], Support vector machine [7], algorithm with filtering techniques such as the wavelet transform [14], [18]. And texture features extraction have been used in several image analysis applications including texture classification and segmentation [2], image recognition [19], [10], image registration, and motion tracking [16]. A good starting point can be found in [8] which reviews the techniques applied for the development of automatic pavement distress detection and classification system. They also propose a novel approach according to the following major steps: region based on image enhancement, to correct nonuniform background illumination and a skeleton analysis algorithm to classify pavement surface distress types. A multi- scale approach using Markov Random Fields for crack detection is presented in[20]. Cracks are enhanced using a Gaussian function and then processed by a 2D matched filter to detect cracks. Another approach, based on a non sub-sampled contour-let transform for pavement distress crack detection, is proposed in [21] but few experimental result are provided. There are many different approaches for road pavement defects detection. One of the simplest approach is performed by analysis of the histograms using artificial neural networks (ANN). In [3] authors proposed a presented a neural network based technique for the classification of segments of road images into cracks and normal images. The density and histogram features are extracted. The features are passed to a neural network for the classification of images into images with and without cracks. Once images are classified into cracks and non-cracks, they are passed to another neural network for the classification of a crack type after segmentation. Graphical model widely used for segmentation, in [5] authors employed Markov graphical model to highlight defects that maximizes the similarity with elementary wavelets and Gaussian-E models. In [6] authors suggested to combine methods of mathematical morphology and Fourier transform to generate features which have been classified using morphological transformed image, texture and Fourier signatures based on classifier AdaBoost [9]. In [12] authors proposed two novel methods for road lane marking and road surface artifacts detection. These algorithms are developed for video-based road registration and monitoring system, which is car-mounted complex for data gathering and analysis of road surface. Detection is performed on rectified images of road surface, constructed from video sequences from driving vehicle. A new method of road lane marking detection is based on machine-learning approach. The algorithm applies over segmentation method to images and then classify the regions using classifier cascades. In [11] Lempert, Sidorov and Zhukov presented an approach to the problem of prioritization work on repairing the pavement with limited resources, which is to use a combination of methods for identification and classification of defects on the basis of statistical analysis and machine learning (Random Forests) with original methods for solving the infinite-dimensional optimization (optical - geometrical analogy). The whole process is tested both on a textural recognition task based on the VisTex image database and on road images collected by a dedicated road imaging system.

3 Defects Detection and Classification Method on Road Pavement

Our goal is find the most efficient method using combination of different kind of features (Histogram, CCH - Histogram chain code, Moments-hull, shape of features) and machine learning algorithms (MRF- Markov random fields, Random forest method).

3.1 Feature Extraction

We propose to preprocess images before the feature extraction. First we apply noise filtering using Gaussian filter and convert to gray scale images. On the next step we perform image segmentation. We propose divide the image into separate regions. Then we separate pixel defects to detected a connected region. We use morphological method to detect pixels corresponding to defects and to remove small regions which are considered as noise. We consider the following defects.
Block crack: Interconnected cracks forming a series of blocks approximately rectangular in shape, commonly distributed over the full pavement. Attributes of block crack defect are: Predominant crack width (mm), predominant cell width (mm), area affected (m^2).
Longitudinal Cracks: Unconnected crack running longitudinally along the pavement. Attributes of Longitudinal Cracks defect are Crack width (mm), Crack length (m), Crack spacing (mm), Area affected (m^2).
Potholes: Irregularly shaped holes of various sizes in the pavement. Attributes

of Potholes defect are depth of potholes (mm) and area of pothole (m^2).
From the analysis of the attributes of each defect, we selected the following features:
Hu-moments: The most notable are Hu-Moments which can be used to describe, characterize, and quantify the shape of an object in an image. Hu-Moments are normally extracted from the shape of an object in an image. By describing the shape of an object, we are able to extract a shape feature vector (i.e. a list of numbers) to represent the shape of the object. We can then compare two feature vectors using a similarity metric or distance function to determine how 'similar' the shapes are.
Chain code histogram : The chain code histogram (CCH) is meant to group together objects that look similar to a human observer[22]. It is not meant for exact detection and classification tasks. The CCH is calculated from the chain code presentation of a contour.
The Freeman chain code [23] is a compact way to represent a contour of an object. The chain code is an ordered sequence of n links $\{c_i, i = 1, 2, .., n\}$, where c_i is a vector connecting neighboring contour pixels. The directions of c_i are coded with integer values $k = 0, 1, ..., K - 1$ in a counterclockwise sense starting from the direction of the positive $x - axis$. The number of directions K takes integer values2^{M+1} where M is a positive integer. The chain codes where $K > 8$ are called generalized chain codes [24].
The calculation of the chain code histogram is fast and simple. The CCH is a discrete function:
$p(k) = n_k/n, k = 0, 1, ..., K - 1,$
where n_k is the number of chain code values k in a chain code, and n is the number of links in a chain code. Beside we consider also size of defect region (width and length, area) and histogram of image.

3.2 Construction of Map of Defects

To automatically label regions defect/non defect, a pattern recognition system operating over a simple feature space is proposed. The feature space is multi-dimensional, in this problem we build 4 dimensional, being constructed using regions local statistics, computed for normalized and saturated images. The first features is the mean value of all pixel intensities in a region. The second is chain code histogram, third is Hu-moment used to describe, characterize, and quantify the shape of an object in an image. Fourth is size of defect region (width and length, area) and histogram of image.
The first aim is to split the image database into two subsets: the training images set, used to train classifiers with manually labeled samples(images regions) containing defect pixels. The testing image set, the remaining images are supposed to be automatically processed by program for defect pavement detection and defect pavement types classification.
Defect pavement detection, where image region are labeled as containing defect pixels or not, and defect pavement type classification, where “Block crack”, “Longitudinal Cracks”, “Potholes” labels are assigned to each detected defect

pavement. For defect pavement detection, an initial setup is required where operator selects images used to determine an optimum set of detection parameters accounting for pixel-by-pixel gray scale variation as related to defect pavement contrast, brightness, and surface conditions. During this setup phase, the program provides visual feedback of the detection results in the form of defect maps traced over the underlying images of control pavements.
These defect maps provide instant feedback on the efficiency of the parameters. Through an iterative process, the optimal detection parameters are selected for each control pavement. Once the settings are selected, our program is programmed to automatically process the pavement images to detect defects pavement. For each defect, the length, width, and orientation are computed and saved. An example is a digital defect map as shown in Fig.1a demonstrates defect map corresponding to images shown on Fig.1b. To improve quality of image

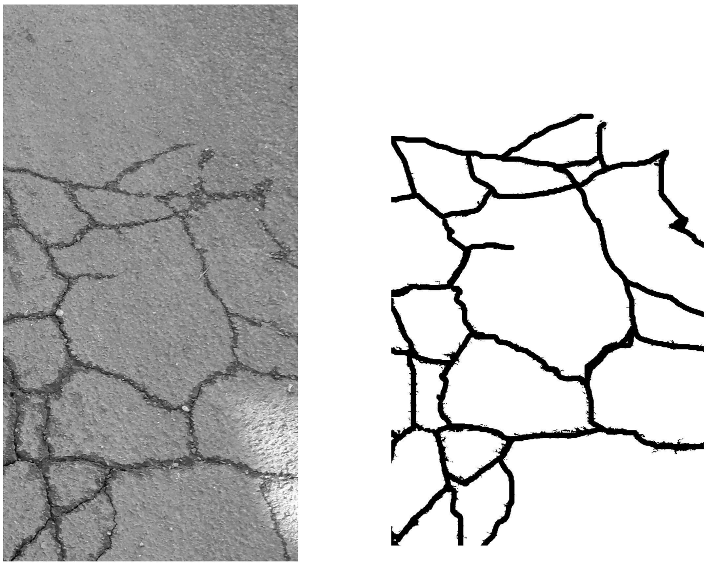

Fig. 1. a: digital pavement image, b: Defect pavement map.

segmentation(Fig.2), with a Markov Random Field[25] is used.

These segments are called "sites" and have a predefined orientation of 0, 45, 90 or 135 degrees. The separation between both cases is done with parameter $k \in (0, 1)$. Our goal will be to segment an image by constructing a graph such that the minimal cut of this graph will cut all the edges connecting the pixels of different objects with each other.

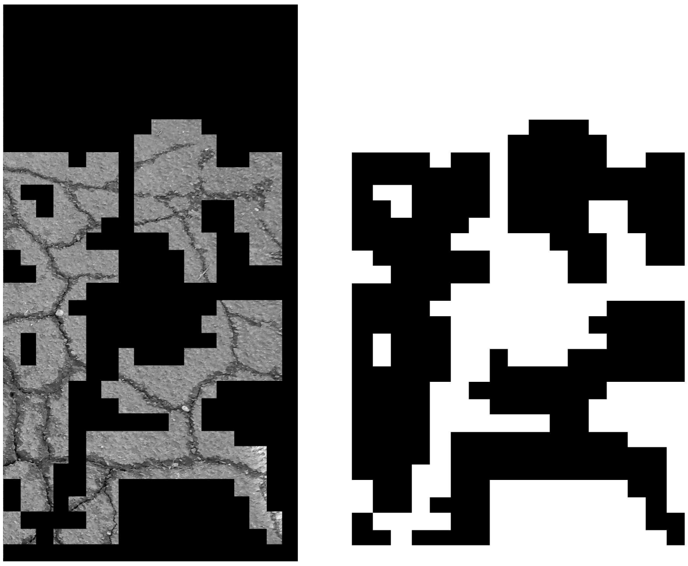

Fig. 2. Defect pavement image segmentation.

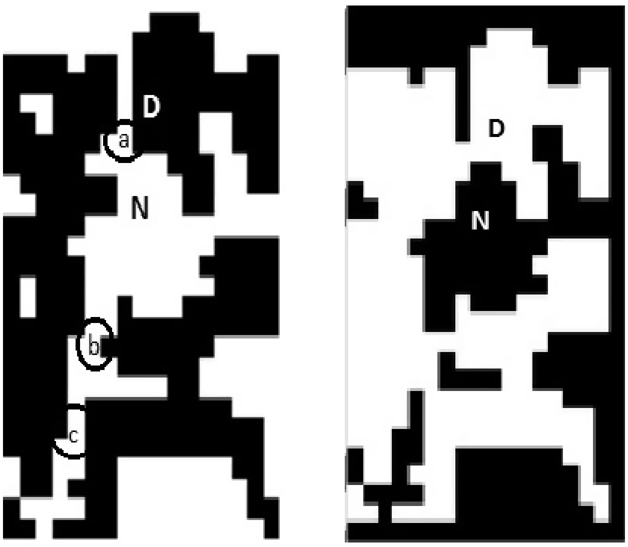

Fig. 3. Use Graph cut to improve image segmentation.

1.Start with an arbitrary labeling f
2.Set success := 0;
3.**for** *each pair of labels* $D, N \subset L$ **do**
  Find $\hat{f} = argminE(\acute{f})$ among $\acute{f}$ within one $D-N$ swap of f;
  if $E(\hat{f}) < E(f)$ **then**
    set $f := \hat{f}$;
    success := 1;
  end
end
4.**if** *success = 1* **then**
  goto 2;
end
5.Return f

Algorithm 1: Steps of Graph cut method

We applied efficient graph based method to find the optimal D(Defect)-N(Not defect) as shown in Fig.3 swap or D - expansion given a labeling f. We use graph cuts to efficiently find $\hat{f}$[27],[26]. Let us briefly outline the approach we used. Let $G = \langle V, E\rangle$ be a weighted graph with two distinguished verticals called the terminals. A $cutC \in E$ is a set of edges such that the terminals are separated in the induced graph $G(C) = \langle V, E - C\rangle$. In addition, no proper subset of C separates the terminals in $G(C)$. The cost of the cut C, denoted $|C|$, equals the sum of its edge weights. A graph-based approach makes use of efficient solutions of the maxflow/mincut problem between source and sink nodes in directed graphs. To take advantage of this we generate an s-t-graph as follows: The set of nodes is equal to the set of pixels in the image. Every pixel is connected with its d-neighborhood ($d = 4; 8$). The minimum cut problem is to find the cheapest cut among all cuts separating the terminals. Minimum cuts can be efficiently found by standard combinatorial algorithms with different low-order polynomial complexities[29]. Our experimental results have been obtained using a new max-flow algorithm that has the best speed on our graphs over many modern algorithms[30]. The running time is nearly linear in practice. Some results of segmentation of classes defect road pavement are shown in Fig.4

3.3 Defect on Road Pavement Classification

This section describes the classification based on unsupervised learning method approach(Fig.5): Random Forest[4]. A random forest algorithm takes the decision tree concept further by producing a large number of decision trees. The approach first takes a random sample of the data and identifies a key set of features to grow each decision tree. These decision trees then have their Out-Of-Bag error determined (error rate of the model) and then the collection of decision trees are compared to find the joint set of variables that produce the strongest classification model. All Database of training images features compose a pattern vector feature x, representing a sample of the random variable X, taking values on a sample space X. For each element x_i of pattern vector x, one possible class

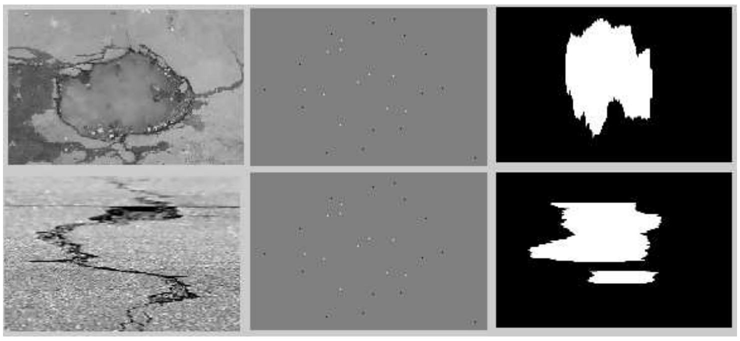

Fig. 4. Results of segmentation of classes defect pavement.

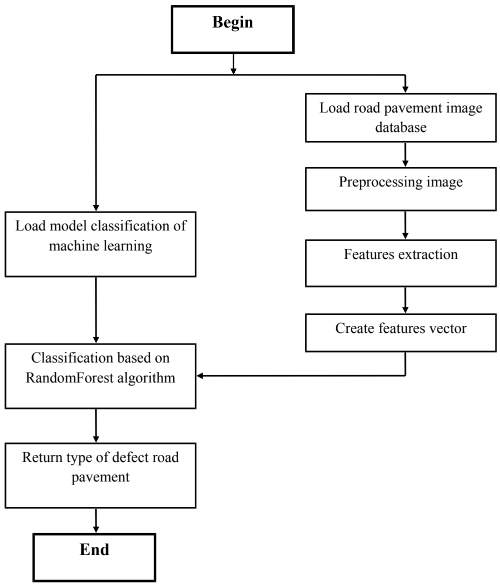

Fig. 5. Defect of pavement classification flow-chart.

y_i is assigned, where Y is the class set, $y_i \in Y$. The training set is:
$T = \{(x_1, y_1) ... (x_n, y_n) : x_i \in \mathbb{R}^2; y_i \in \{c_1, c_2 ..., c_n\}\}$
Where n is the number of points of the pattern vector x.
The Random Forest classifier was built using the package Random Forest 4.5-16 for the R statistical environment [31] to classify feature vectors as defect or non-defect.The training set consists of 500 images (200 of class 'defect' and 300 of class 'non-defect'. In 200 images of class defect included 150 images(50 Block images, 50 Longitudinal images, 50 Pothole images) for training process and 50 images for testing process. In 300 images of class non-defect included 200 for training process and 100 images for testing process. Our dataset images were builded by Center for Telecommunications and Multimedia, INESC TEC, Portugal. Beside we use own our dataset, which is collected by camera (Canon D100 16 mega pixel). Images are captured in conventional daylight condition, distance from camera to surface of road is 1m-1.2m.
Imbalanced data follows the idea of cost sensitive learning make random forest more suitable for learning. Class weights are an essential tuning parameter to achieve desired performance. In the tree induction procedure, class weights are used to weight the Gini criterion for finding splits. In the terminal nodes of each tree, class weights are again taken into consideration. We introduce the concept[28]: True Positive – TP is classified correctly as positive, True Negative - TN is classified correctly as negative, False Positive - FP is classified wrongly as positive, False Negative – FN is classified wrongly as negative. For Random Forest algorithm, there is always a tradeoff between true positive rate and true negative rate and the same applies for recall and precision.
True nagative rate $= \frac{TN}{TN+FP}$, True Positive rate $= \frac{TP}{TP+FN}$, Precision $= \frac{TP}{TP+FP}$
The classifier was trained on pavements road dataset using Chain code histogram

Table 1. Best model for classification depends upon the precision,true positive rate, false positive rate

Class	True Positive	False Positive	Precision
Potholes	0.903	0.556	0.843
Block crack	0.80	0.726	0.880
Longitudinal cracks	0.947	0.230	0.926

- CCH, Hu moments, size of defect for each variant. We also used method Boosting(GBTs) to classify this dataset and to compare results from two classification methods. The main difference between these two algorithms is the order in which each component tree is trained.

The classifier was built using the parameters $ntree = (50, 100)$ and $mtry = 2$ and $depth = (2, 5)$.
In table 2 shows the effect of increasing the number of trees in the ensemble. For both, increasing trees require more time to learn but also provide better results in terms of Mean Squared Error (MSE) is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(f\left(x_i\right) - y_i\right)^2$$

Where n is the number of test examples, $f\left(x_i\right)$ the classifier's probabilistic output on x_i and y_i are actual labels.
Random Forests are fast to train, but they often require deep trees. Random Forests do not overfit as easily, but algorithm's test error plateaus. Our experiments show that more trees are always better with diminishing returns. Deeper trees are almost always better subject to requiring more trees for similar performance. The above two points are directly a result of the bias-variance trade off. Deeper trees reduces the bias; more trees reduces the variance. There are several ways to control how deep our trees are (limit the maximum depth, limit the number of nodes, limit the number of objects required to split, stop splitting if the split does not sufficiently improve the fit, ...). Most of the time, it is recommended to prune (limit the depth of) the trees if we are dealing with noisy data. Finally, we can use our fully developed trees to compute performance of shorter trees as these are a "subset" of the fully developed ones.

Table 2. Training time, Correct rate and Error test of classification algorithms: Random Forest and Boosting(GBTs)

	Random Forest		Boosting(GBTs)	
	Trees:50 Depth:2	Trees:100 Depth:5	Trees:50 Depth:2	Trees:100 Depth:5
Training time(sec)	150	257	140	278
Correct rate(%)	80.5	93.29	88.57	91.45
MSE	0.393	0.366	0.3	0.516

4 Conclusions

In this article we suggested the novel approach for road pavements defects automatic detection and classification. A simple boosting method is used to train the classifier and the two sets (one for each road) make it possible to achieve results which demonstrates the robustness of the implemented method and algorithm for pavement crack detection based on Markov Random Fields. This method is based on the construction of an irregular lattice derived from the original image. The lattice is composed only by straight line segments. Firstly a local linear detection and an irregular lattice construction is done in order to highlight linear features locally.
We also propose to use to Graph cut method, which improve quality of image segmentation. From this we can detection part of pavement defect - non defect. The classification algorithm - Random Forest was able to correctly classify all

the images contained in the two first sets. In the test set simulating the real environment the achieved classification results were 95,5% which are very good. The authors are grateful to the attention and guidance of Prof. Dr. D. N. Sidorov. Authors are thankful to Center for Telecommunications and Multimedia, INESC TEC, Portugal for providing the dataset.

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