Pavement Distress Detection Using Random Decision Forests

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Abstract. Pavement distress detection is a key technology to evaluate pavement surface and crack severity. However, there are many challenging problems when using pavement distress detection technology to do road maintenance, such as the inference of textured surroundings with similar intensity to the distresses, the existence of intensity inhomogeneity along the distresses and the requirement of real-time detection in practice. To address these problems, we propose a novel method for pavement distress detection based on random decision forests. By introducing the color gradient features at multiple scales commonly used in contour detection, we extend the feature set of traditional distress detection methods and get the represented crack with richer information. During the process of training, we apply a subsampling strategy at each node to maintain the diversity of trees. With this work, we finally solve all the three problems mentioned above. In addition, according to the characteristics of random decision forests, our method is easy to parallel and able to conduct real-time detection. Experimental results show that our approach is faster and more accurate than existing methods.

1 Introduction

Pavement distresses, usually in the form of cracks, reduces the road performance and constrains passing vehicles [17]. Under this circumstance, road maintenance equipment are required, which relying on effective pavement distress detection system. The traditional manual methods are time-consuming, dangerous and labor-intensive [6], on the contrary, automatic pavement distress detection becomes an active area. Remarkable achievements [4,5,31] have been made in this field. However, the real-time distress detection still remains challenges. Some methods have very low processing speed or low accuracy. Others only deal with certain types of distress.

With the development of machine learning, methods based on neural network [11], Markov random field [7] and wavelet [26] are introduced in this

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area successively. Machine learning shows promising performance in distress detection. It captures the distinguishing features of distress, and it is adaptive to tasks. In these methods, images are divided into small blocks. Common used features such as mean and standard values are computed on these blocks. But these methods may generate a set of disjoint fragments instead of complete crack curves, due to noises such as textured surrounding or oil spot.

In this paper, we propose a novel pavement distress detection method based on random decision forests. Due to its flexibility, efficiency and good generalization ability, random decision forests have been using broadly in the image processing area [2,25]. The training of each tree is independent, so the algorithm is easy to paralleled and very fast. Here we use two kinds of features: the common used features such as mean and standard deviation value and color gradient feature over multiples scales. These features can characterize distress region much better.

A series of experiments are conducted to test the performance of our proposed method. We test our method under different scales of training data, and compare our method with state-of-the-art pavement distress detection methods. The results show that our method is promising.

2 Related Work

There have been many methods proposed for pavement distress detection. In this section, a brief review of pavement distress detection is given. A recent research of evaluating multiple pavement distress detection can be found in [29].

Some researchers [12,15] apply the intuitive idea that the defect region is darker than its surroundings. These methods are straight-forward, but noises such as the water stain or the shadow may negatively affect the general precision. Method [1] tries to improve the performance of Sobel using bidimensional empirical mode decomposition (BEMD). But this method may not handle well the cracks with poor continuity.

In recent years, machine learning methods also show great robustness in distress detection. In literature [11], artificial neural network models are used in automatic thresholding of the images and in the classification stage. In literature [7], a crack image is projected onto a regular lattice, which allows the definition of a Markovian crack model. Wavelet-based method [30] uses wavelet transform to separate distresses from noises. However, this method can not detect cracks with high curvature or potholes with complex topology.

In addition, some block-based methods extract small patches from the original images and calculate features on these patches. For example, literature [27] uses a morphology method to describe a succession of cracks. Literature [10] uses longitudinal, transverse and diagonal crack seed to connect the detected regions. However, these methods may generate a set of unconnected regions instead of a complete distress. In order to overcome the above shortages, CrackTree [31] conducts recursive edge pruning in the minimum spanning tree (MST) to improve the continuity of the detected cracks. Features used in these methods are quite intuitive, such as mean, standard deviation, width of boundary rectangle, difference of mean and standard deviation of two cells on each side of the connected region [14]. We assume these features can not capture the overall information of distresses. Since the distress detection method can be considered as a specific contour detection problem, the features commonly used in contour detection are introduced in our method.

In general, the existing methods do not perform well in detecting complete crack curves. And the noise background also brings challenges to the distress detection. We apply a large pool of features which can capture the distress from various aspects to bridge this gap. In addition, since multiple decision trees can be trained and applied simultaneously, our method shows promising processing speed. Besides, as a boosting framework, other methods such as MCLP [23,24] and SVMs [20–22] can be used in it.

3 Automatic Pavement Distress Detection

In this section we begin with a brief review of random decision forests [9,13], and then introduce our method in details.

3.1 Feature Extraction

Suppose we have a set of image I with a corresponding set of manually labeled sketches G which indicates the edge of distress regions. 16×16 image patches $x \in \mathcal{X}$ are extracted from the original images using a sliding window. Features are computed on these patches.

Many existing methods [14,16,18] use mean and standard deviation value as features. Two matrices are computed for each original image: the mean matrix M_m with each block's average intensity and standard deviation matrix STD_m with the corresponding standard deviation value std. These feature are computed on gray level image. And they can't characterize the distress comprehensively. Inspired by Dollá et al. [9], we also apply a large set features at multiple scales, orientations and so on. These features tend to be much more general. As a result, applying the method to another domain is straightforward. Which kind of crack can be detected by this method mainly depends on the training set.

3.2 Training Random Decision Forests

Random decision forests have successfully applied in many fields such as image labeling [13], object categorization [28] and image segmentation [25]. The method is extremely fast for the training and tend not to overfit.

Training Stage: We extract image patches by using a sliding window and compute its features. Next, a weak classifier is trained at each node to decide whether a pixel is in a defect region or not according to a certain probability. Given a trained tree, a pixel is routed recursively left or right until a leaf is reached. Individual tree tends to overfit, random decision forests bridge this gap by merging multiple decision trees together.

A subsampling strategy is applied to maintain the diversity of trees. Each tree $T \in \mathcal{F}$ is trained independently on a random subset of the training set $\mathcal{D} \subseteq \mathcal{X} \times \mathcal{Y}$. A decision tree can predict the class of a sample $x_i \in \mathcal{X}$ by branching it left or right until a leaf is reached. Each sample is passed to the left or right subtree, weighted by $q(-1|x_i)$ and $q(+1|x_i)$ respectively, where $q(+1|x_i)$ denotes the probability that x_i is a positive sample.

The node of tree is characterized by two functions: $q(-1|x_i)$ and $q(+1|x)$. The sample x is routed to the left decision sub-tree t_l if $q(-1|x_i) - \frac{1}{2} > \varepsilon$, or to the right decision sub-tree t_l if $q(+1|x_i) - \frac{1}{2} > \varepsilon$, where ε is a threshold. Besides, if the sample is near the decision boundary, it is passed to both sub-trees.

Computing Probability: Given a trained tree, the probability $p(y|x)$ that sample x belongs to class y is defined recursively:

$$p(y|x) = q(+1|x) \cdot p_r(y|x) + q(-1|x) \cdot p_l(y|x) \tag{1}$$

where $p_l(y|x)$ and $p_r(y|x)$ are posteriors of the left and right trees.

The final prediction of a sample $x \in \mathcal{X}$ given a forest $\mathcal{F}$ can be obtained from the individual tree predictions:

$$\overline{p(y|x)} = \frac{1}{N} \sum_{t \in \mathcal{F}} p_t(y|x) \tag{2}$$

where N indicates the total tree number in the forest.

3.3 Binarization

The output of the above stage yields the probability of each pixel being in a distress region. The pixels in distress regions tend to have the high probability, others tend to have the low probability. A threshold θ_1 is introduced to remove the distress free regions. The noises such as shadows or texture surrounding can be eliminated effectively after the above section. But water stain and oil spot may not be removed throughly. We use another threshold θ_2 to small connected fragments (less than θ_2 pixels).

4 Experimental Results

In this section we compare the performance of our proposed method with Canny [3], BEL [9] and CrackIT [18]. Part of the Matlab code is supported on Piotr's Computer Vision Toolbox [8] and CrackIT [19]. The experiments are conducted on a pavement surface image database proposed by Oliveira et al. [18]. These images are captured during a visual survey along a Portuguese road. To obtain the ground truth, we outline the distress in each image using a image annotated program. All experiments are conducted on a desktop with AMD FX(tm)-4300 Quad-Core Processor and 4G RAM.

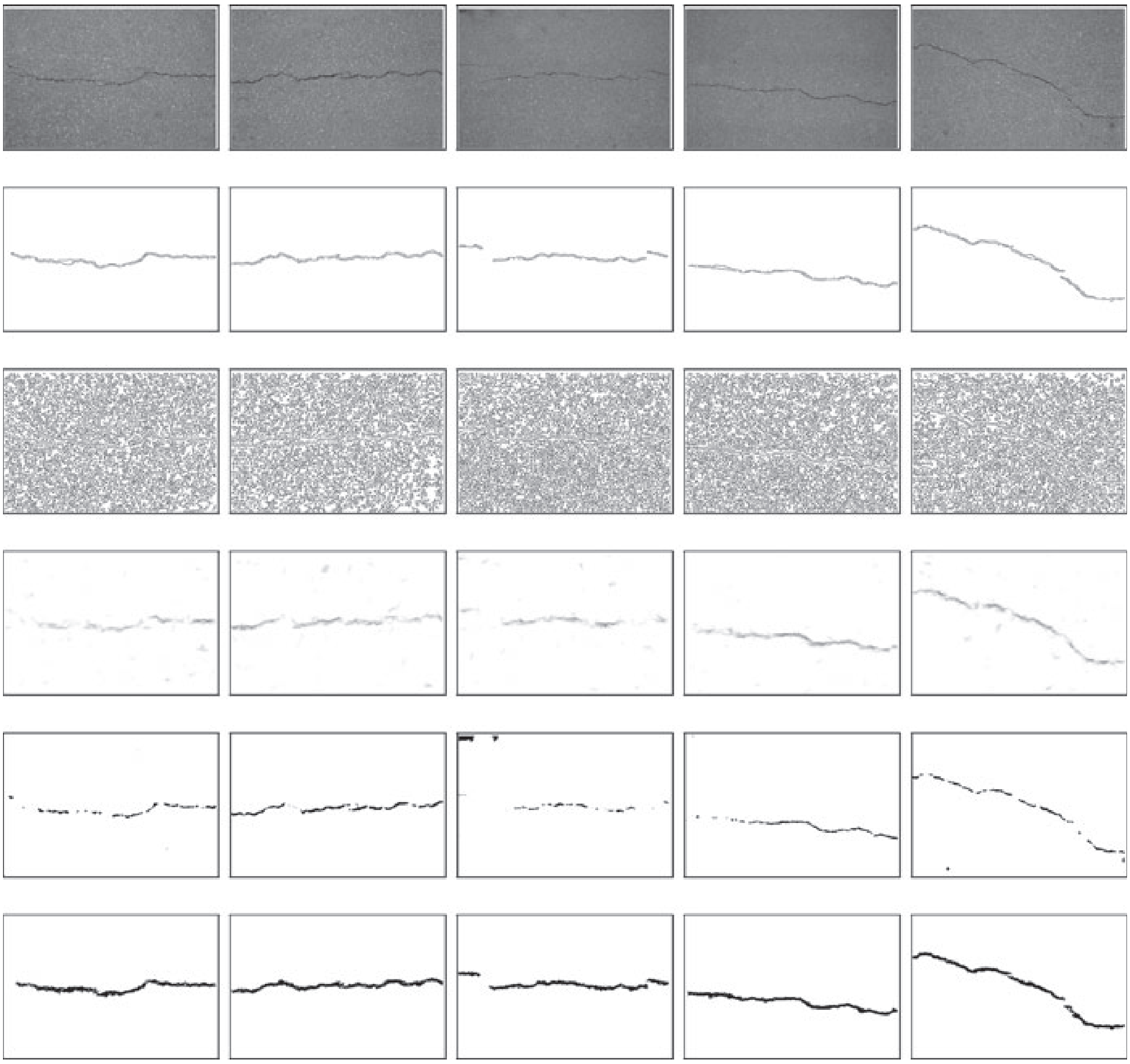

Fig. 1. Pavement distress detection results on four algorithms. (From top to down: Canny, BEL, CrackIT and our method.)

Fig. 2. Precision, Recall and F1 Score of various methods.

Figure 1 shows the results on five sample images. Our method has preserved most of the real distress regions with high continuity. Noises and textured background are suppressed. Other methods are suffered from the interferences of discontinuous fragments and various noises.

Figure 2 shows the average performance of different methods. Our method has higher precision, recall and F1 score than other methods, and clearly outperforms all alternative methods.

5 Conclusion

In this paper, we propose an automatic pavement distress detection method. Our innovation is as following shown: Firstly, the introducing of random decision forests makes it possible to compute the probability of each pixel being in a distress region. Secondly, to capture various facets of the pavement distress, we apply multiple features commonly used in object contour detection to enrich the feature of traditional distress detection set. Thirdly, a subsampling strategy is applied to maintain the diversity of trees and prevent overfitting. In addition, our framework has powerful learning ability. Our method shows promising processing speed and state-of-the-art accuracy in all experiments.

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