Road Surface Cracks Detection Using Unsupervised Strategies

Henrique Oliveira, Paulo Lobato Correia
Instituto de Telecomunicações – Instituto Superior Técnico
hjmo@lx.it.pt, plc@lx.it.pt

Abstract

This paper describes and compares two unsupervised classification strategies to detect cracks on flexible road pavement surface images. The first strategy uses a Bayesian classifier; the second is based on one-class classifiers. A simple two dimensional feature space is considered, exploiting the mean and the standard deviation of the pixel's gray levels, computed for non-overlapping image regions. For both strategies a bivariate class-conditional normal density is adopted, for stochastic data modeling, as it produces a good description of the data. Several normalization steps are proposed, to achieve better final results. Experimental crack detection results are presented based on real images taken from Portuguese roads.

1. Introduction

To support a correct highway infrastructure maintenance policy, automatic systems for fast and reliable pavement surface defects analysis are being developed, instead of relying solely in the slow and subjective traditional human inspection procedures [1].

An image based pavement surface distress survey system poses some challenges, because complex data processing techniques are needed due to the variability of pavement conditions and textures. Neural networks, Markov random fields or edge detection approaches have been reported in the literature [1] [2]. Here, Bayesian and one-class classifiers are investigated for crack detection, envisaging the use of a pattern recognition system for this type of application.

This paper is organized as follows: section 2 describes the proposed unsupervised crack detection strategies. Section 3 presents experimental results while section 4 draws conclusions and presents some hints for future work.

2. Proposed crack detection strategies

An overview of the proposed unsupervised crack detection system architecture is show in Figure 1.

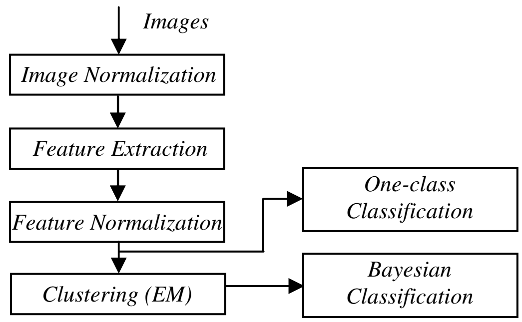

Figure.1. Proposed unsupervised crack detection system architecture

2.1. Normalization and feature extraction

The grayscale images processed in the scope of this work were captured by a human operator during a visual road survey, using a digital camera with its optical axis perpendicular to the pavement surface. Images sizes range from 2048×1536 to 1858×1384 and are processed at region level, with each image being divided into non-overlapping 75×75 pixel regions.

The images present some imperfections even in areas of perfect pavement condition: a non-uniform illumination due to the type of sensor used and some pixel intensity variability in non-crack regions originated by specular reflection of some road surface materials.

The first step to minimize those image imperfections is to compute a reference gray level for each image, taken as the mean of all its pixel's gray levels. Image normalization is then performed at the region level, ensuring that all regions in each image present the same reference gray level. Next, to reduce the variability of pixel intensities on the previously normalized images (like the specular reflections caused by some pavement surface materials), a pixel intensity saturation removal procedure is implemented. This module replaces all pixel intensities with values above the computed average intensity by that average value, while the other pixels remain unchanged. These two normalization procedures help achieving better classification results, since it reduces the standard deviation (*std*) of pixel intensities in regions without cracks (brighter pixels), without significantly affecting the values computed for those regions containing crack pixels (darker pixels).

At this stage, a two dimensional (2D) feature space is constructed for each image based on two simple but effective features: the mean and *std* of pixel intensities within each region.

Now, another normalization step is proposed, on the feature space, to reduce the feature representation scattering between database images, which would influence negatively the classification results. For each image, the centroid of its 2D feature space is calculated. Then, a global centroid is computed, based on the full set of images and, for each individual image, the corresponding 2D feature space points are translated so that its centroid will coincide with the global centroid.

2.2. Unsupervised Bayesian classification

Since this paper deals with unsupervised strategies, the 2D feature space is initially unlabelled, with each feature point representing the measurements computed for an image region, i.e. the mean and the *std* of region pixel intensities.

All the measurements for each image compose a pattern vector **x**, representing a sample of the random variable **X**, taking values on a sample space ***X***. For each element x_i of the pattern vector **x** one possible class y_i is assigned, where **Y** is the class set. Thus, the training set is:

$$\mathrm{T} = \{(x_1, y_1)\ldots(x_n, y_n) : x_i \in \Re^2;\, y_i \in \{c_1, c_2\}\}, \quad (1)$$

where n is the number of points for the pattern vector **x**. We assume y_i as a hidden variable. Only two classes are used: regions without cracks, labeled as class c_1, and regions with cracks, labeled as class c_2.

The Bayesian classification approach used here needs to be supplied with the joint distribution of the two classes. Thus, training and test sets are created, the first being used for classifier learning. The training set is selected from the image database by a skilled road inspector, who empirically chooses images with evident pavement cracks. The remaining images compose the test set.

An automatic clustering analysis algorithm can then be used to label the data, leading to an unsupervised strategy. A bivariate class-conditional normal density is used for both strategies presented in this paper, as it allows a good representation of the measurements. As such, the expectation-maximization algorithm (EM) is selected to estimate the parameters for a Gaussian mixture model, with general covariance matrices, modeling the two dimensional feature space. After that, the following decision rule is applied [3]:

$$p(\mathbf{x} \mid y_i = c_1)P(y_i = c_1) \underset{c_2}{\overset{c_1}{\gtrless}} p(\mathbf{x} \mid y_i = c_2)P(y_i = c_2) \quad (2)$$

with the class priors $p(y_i=c_k)$, where $_k$ stands for the class index '1' or '2', are calculated according to the expression:

$$p(y_i = c_k) = \frac{\#\text{ measurements labeled into class } c_k}{\text{total number of measurements for all classes}} \quad (3)$$

2.3. Unsupervised one-class classification

For the second classification strategy proposed only one class is considered and the goal is to seek a boundary decision which separates the class points (target – regions without crack pixels) from its outliers (regions with crack pixels). Here, the density method approach was selected, among others, as it works well when the sample size of the target class is large enough (which is the case) and a flexible distribution model is used (like the Gaussian model) [4].

The mean vector $\boldsymbol{\mu}$ and the covariance matrix $\boldsymbol{\Sigma}$, are estimated using the standard maximum likelihood (ML,

$$\hat{\boldsymbol{\mu}} = \frac{1}{n}\sum_{i=1}^{n} x_i \text{ and } \hat{\Sigma} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{\boldsymbol{\mu}})(x_i - \hat{\boldsymbol{\mu}})^{\mathrm{T}}, \quad (4)$$

and a measurement is considered to be an outlier if:

$$\begin{cases} x_i \text{ is outlier if } (x_i - \boldsymbol{\mu})^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (x_i - \boldsymbol{\mu}) > \varepsilon \\ \text{otherwise } x_i \text{ is a detected target} \end{cases} \quad (5)$$

The threshold ε (empirical selected after exhaustive trials made during the training stage of the classifier and considering different training sets) is chosen to achieve a certain portion of the measurements being excluded from the target class, i.e., classified as outliers [5]. The computation of the parameters $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ is iterated until condition in (5) is satisfied.

3. Experimental results

The value for the threshold ε adopted in (5) was 10%, empirically chosen after exhaustive trials made during the training stage of the one-class classifier and using different training sets. Part of the Matlab algorithmic implementation was supported on the PRtools [6] and DDtools [5] toolboxes.

Since a general covariance matrix was adopted in both classifiers, the boundary decision is quadratic [7] and Figure 2 shows the decision boundaries obtained at the training stage, superimposed over the ground truth data for the training set images, where classes c_1 and c_2 points are show respectively in red and blue colors

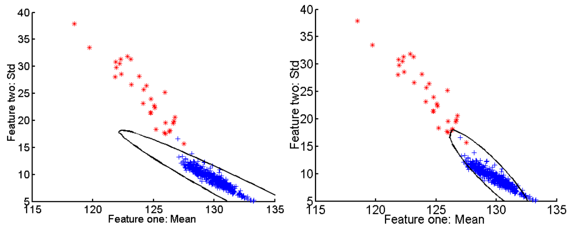

Figure.2. Plot of the EM-bayesian (left) and one-class classification (right) decision boundaries obtained during training stage, superimposed to ground truth data.

Figure 3 shows samples of the experimental results obtained for the unsupervised strategies being proposed, where 5 images with relevant cracks were empirically chosen by a skilled road inspector for classifiers training and the remaining 51 (in a total of 56 images) were used for testing. Results show that the one-class classifier approach tends to detect more false positives, although presenting a good true positives detection rate. The approach based on the EM clustering and Bayesian classification performs better both in terms of false and true positives.

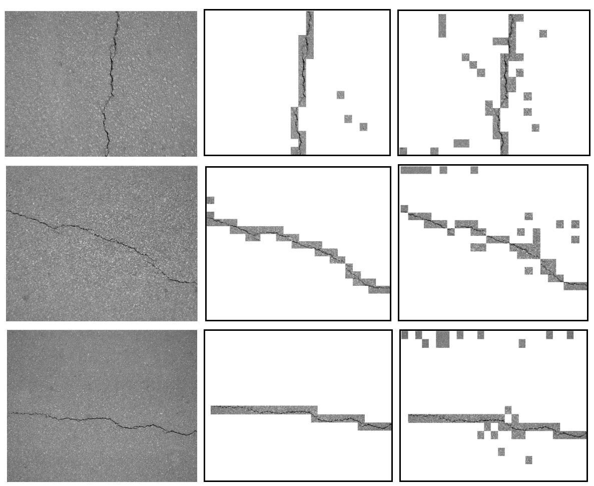

Figure.3. Original image (left); bayesian (middle) and one-class (right) classification results.

Since a ground truth (manually created by a human operator who identified those regions containing cracks) was available for the entire image database used, it was possible to compute mean error rate (ME), precision and recall measurement values for windows classified as containing cracks, as well as a derived performance criterion during test stage, reflecting the overall classifier performance [5], defined as:

$$PC = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \,. \qquad (6)$$

Evaluation results are shown in Table 1. Especially for precision and recall metrics, the most important ones for this proposed application, the following values were achieved: 89% and 97.0% for EM-Bayesian: 91% and 54% for the one-class classification, respectively.

Table 1 – Results for the detection of regions with crack pixels.

	ME	Precision	Recall	PC
Bayesian	3.0%	89.0%	97.0%	92.8%
One-class	10.2%	53.4%	90.7%	67.1%

4. Conclusions and future work

This paper confronts two unsupervised strategies, EM-Bayesian and one-class classification for road crack detection. The first achieved very promising results, while the second presents more false positives, having difficulty to deal with long tailed data distributions, which implies the need of an additional validation step, to remove the unwanted false positives.

The use of unsupervised strategies when compared to the supervised ones is emphasized here, since it could be helpful especially in cases when changes in road pavement surface texture arise, because the distribution function that models the data could change in that situation but a good data clustering ability remains.

As future work, the consideration of a reject-option for the Bayesian approach, a non uniform loss function, or the usage of one-class classifiers capable of dealing with long tailed data distributions, will be explored.

5. References

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