Computer Vision Based Detection and Localization of Potholes in Asphalt Pavement Images

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***Abstract*— Asphalt pavement distresses have significant importance in roads and highways. This paper addresses the detection and localization of one of the key pavement distresses, the potholes using computer vision. Different kinds of pothole and non-pothole images from asphalt pavement are considered for experimentation. Considering the appearance-shape based nature of the potholes, Histograms of oriented gradients (HOG) features are computed for the input images. Features are trained and classified using Naïve Bayes classifier resulting in labeling of the input as pothole or non-pothole image. To locate the pothole in the detected pothole images, normalized graph cut segmentation scheme is employed. Proposed scheme is tested on a dataset having broad range of pavement images. Experimentation results showed 90 % accuracy for the detection of pothole images and high recall for the localization of pothole in the detected images.**

***Index Terms*— Computer vision, pothole detection, histogram of oriented gradient, graph-cut segmentation.**

I. INTRODUCTION

Assessment of asphalt pavement condition is mandatory for the maintenance of road networks. Real time pavement maintenance requires proper and reliable monitoring of the pavement surfaces. A pavement distress is defined as a disorder of pavement structure that reduces serviceability or leads to a reduction in serviceability. Pavement distresses contain symptoms indicating problems of deterioration like Rutting, Fatigue Cracking, Longitudinal Cracking, Transverse Cracking, Block Cracking, Patches, and Potholes. A pothole is a shallow or deep hole in the pavement surface (see Fig. 1) resulting from loss of pavement surfacing material. They may be Bowl-shaped holes of various sizes in the pavement surface. Currently pothole detection is mostly done either through a manual approach by experts or by high-end equipment using 3D reconstruction, stereo-vision, laser and vibration based approaches.

Broadly speaking, the process of pavement condition assessment is divided into three parts. The first step is to collect the data; to a large extent this part is automated. Data collection vehicles are usually loaded with helping equipment like video cameras for surface imaging, optical sensors for distance measurements, laser sensors for longitudinal and transverse profiling and accelerometers for vibration based techniques [1]. Second step is distress identification and classifying the distress type. Last step is distress assessment. Second and third step is usually performed manually which is actually time consuming and cost ineffective. Even though manual evaluations are based on well-defined criteria, a certain amount of subjective measures and the experience of inspection team are required for precise results [2]. An effective approach for sensing the pavement surface with a dedicated inspection vehicle at a speed up to 60mph or approx. 100km/h replacing traditional manual low speed methods is presented in [3]. Unfortunately there is no claim for practical automation of potholes detection except by Pavemetrics [4]. They claim to automatically detect potholes based on 3D data but their performance is not certified anywhere [5].

Computer vision is a science and engineering discipline that aims to make useful automated systems for real physical scenes based on visual data (image / video). These systems can be a good replication of human beings thus reducing the labor costs in most of the environments. Koch and Brilakis [5] presented a novel approach for automated detection of potholes using asphalt pavement surface images. They used histogram-based region segmentation and spot filters [6, 7] for the representation of texture properties of defected and non-defected regions. They further extended their work and deployed the scheme over pavement surface videos instead of images as presented in [8]. But approach lacks to estimate potholes in terms of depth and size. Nejad and Zakeri [9] presented a comparison of wavelet, ridgelet, curvelet based texture features for pothole distress identification. Buchinger et. al. [10] presented a morphological image processing approach for anomalies detection in pavement surfaces. Nienaber et. al. [11] proposed a edge-contour based scheme to warn drivers when potholes detected in real time. Buza et. al. [12] proposed a combined simple thresholding and spectral clustering based scheme for rough estimation of potholes. Jog et. al. [13] presented an approach based on 2D recognition and 3D reconstruction for potholes detection and measurement using monocular camera. A thorough study of existing work clearly indicates about a significant research space for pothole detection in terms of accuracy, illumination impact and shape variant nature of the potholes.

Fig. 1. Examples of Potholes in the Asphalt Pavement [5]

This paper targets to propose a technique for the detection of potholes and subsequently to precisely localize them in the asphalt pavement images. Visual features of road surface are analyzed for classification of images of asphalt pavements as pothole and non-pothole images. The work also addresses to determine the accurate location and shape of the potholes in the classified pothole images. Proposed approach and results are presented in Section II and III.

II. PROPOSED APPROACH

Before proceeding on the proposed scheme, few key observations were considered about the pothole images. A pothole in the asphalt pavement may contain the coarser (dry) or smooth (with water) texture as compared to local neighborhood. Even the overall surface appearance of the pothole cannot be the same due to varying directions of illumination source throughout the day. In addition to these, generally potholes have an elliptical shape. But in ground reality, arbitrary shapes of the pothole are possible due to irregular wear and tear of road surface.

Keeping in view the above observations, a hierarchical top-down approach for the detection and localization of potholes is proposed as shown in Fig. 2. Approach initially targets the identification of the pavement images having one or more potholes, this phase is labeled as *Classification of Pothole/Non-Pothole Images*. Then it proceeds towards the spatial localization of the pothole (s) in the identified images, labeled as *Pothole Localization* phase.

A. Classification of Pothole/Non-Pothole Images

The supervised learning approach is followed for the identification of pothole/non-pothole images. Concise low-level features are computed for all the images during training and testing phases. For feature extraction, all the images are converted from RGB color space to grayscale and resized at 200x200. Image under consideration is labeled as F. Following sub-sections discuss the steps involved in the pothole detection phase:

1) HOG Feature Extraction

Pothole detection problem is considered as a sort of object detection using visual features. HOG feature descriptors [14] are widely used in computer vision for object detection and recognition. HOG is mainly based on the distribution of the edge directions and cumulatively focused on the shape of the object. As concluded earlier, potholes may have no fixed appearances and shapes in the pavement images. Therefore, a local pothole appearance and shape can be represented using HOG feature descriptor. In HOG, first the horizontal and vertical gradients (F_x, F_y) are computed on the image F using following masks:

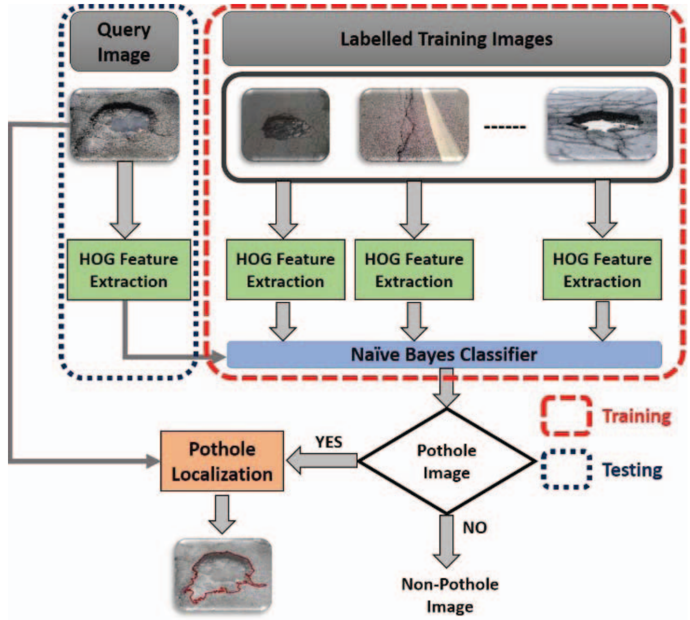


Fig. 2. Algorithmic Workflow

$$M_x = [-1\ 0\ 1]\ and\ M_y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \qquad (1)$$

F_x and F_y gradients are used to calculate the magnitude and orientation of the gradient using following equations:

$$|G|_F = \sqrt{{F_x}^2 + {F_y}^2}\ . \qquad (2)$$

$$\theta = \tan^{-1}(F_y/F_x)\ . \qquad (3)$$

Orientations calculated using (3) are normalized in the range of [0°, 180°] to only focus on the unsigned orientations. Overall image of size 200x200 is divided into 625 (25x25) non-overlapping cells of 8x8 pixels. Each 8x8 cell is further divided into 4 blocks having 4x4 pixels in each block. Then gradient orientations histogram is calculated for each block by quantizing gradient orientations into 8 bins. These 8 bins are evenly spaced over the interval [0°, 180°]. Each pixel has a weighted vote for its corresponding bin based upon the gradient magnitude and orientation. HOG feature extraction resulted in a feature vector V_F of size 1x 20000 (625x4x8). Fig. 3 shows the HOG representation of the given input image. Pictorial representation of HOG also gives a glimpse about the regions which are different from their surroundings w.r.t. appearance and shape.

2) Classification of Feature Vectors

Once the feature vector V_F is computed, next step is to select an accurate classifier for the training and testing purpose. In this scenario, key aim of a classifier is to assign a label (pothole/non-pothole) to the given image keeping in view the trained feature vectors.

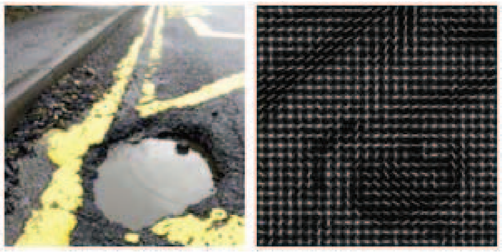


Fig. 3. Input Image and its HOG Representation

Considering the higher scalability and strong independence nature of the features extracted from the images, Naïve Bayes classifier [15] proved to be more suitable for the classification of pothole images. Naïve Bayes assigns the label to an input image based upon the maximum posteriori probability $P\ (C_i|V_F)$ computed as follows:

$$P\ (C_i|V_F) = \frac{P\ (V_F|C_i)\ P\ (C_i)}{P(V_F)} \qquad (4)$$

Where C_i is the class label for i=1, 2 in this scenario i.e. pothole and non-pothole. Feature vector V_F will be labeled as C_i if the probability $P\ (C_i|V_F)$ is the highest among $P\ (C_i|V_F)$ of both the classes. Pothole detection phase resulted in the labeling of an input image as pothole or non-pothole image. If it resulted in a pothole image then the input image is forwarded to pothole localization phase to accurately localize the pothole region.

B. Pothole Localization

Although the indication of an image containing one or more potholes looks sufficient for the highway authorities, but accurate localization of the pothole is also mandatory to explore the regional properties of the potholes. To localize the potholes in the labeled pothole images, image segmentation needs to be carried out based upon some homogeneity criterion.

Pothole segmentation can also be viewed as graph partitioning problem. Keeping in view the variable texture patterns of pothole region, pothole localization is achieved using graph based segmentation using normalized cuts [16]. In graph-cut segmentation, each pothole image is represented using pixel-by-pixel pair-wise similarity matrix based upon intervening contours. In our scenario for segmenting a pothole image, each pothole image is segmented into twelve (12) regions using normalized cuts-based segmentation as shown in Fig. 4 (a). Out of these segmented regions, region having a certain threshold of mean value i.e. less than 80 in this case, is selected as localized pothole as shown in Fig. 4 (b). The same number of segments and mean value is opted for the whole dataset.

III. EXPERIMENTATION RESULTS AND DISCUSSION

The proposed scheme was implemented on the dataset developed by Koch et. al. [5] containing 120 pavement images. Out of 120 images, 50 images are used for training and remaining 70 are used for testing purpose in the pothole detection phase. Experimentation is carried out using MATLAB R12 on a Core i3 machine with 4GB RAM.

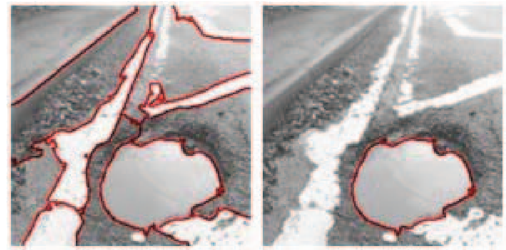
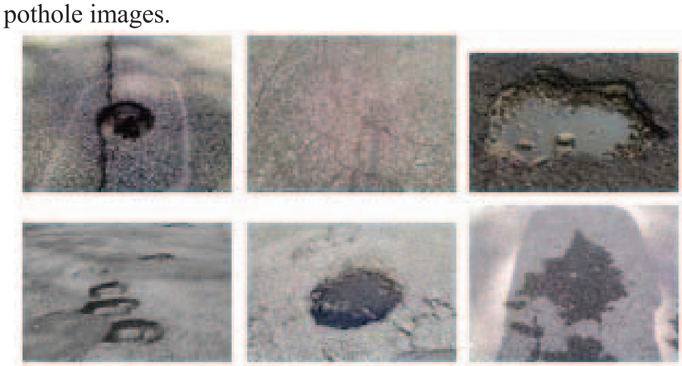


Fig. 4. (a) Normalized Cut Segmentation with 12 segments (b) Refined Results Showing the Pothole Region

In the training phase, HOG descriptor is applied on 50 training images. Resultant HOG feature vectors are passed to the Naïve Bayes classifier for the learning purpose. Once the classifier is trained, the testing images are examined to be declared as pothole or non-pothole image. Fig. 5 shows the HOG representation of selected images from the testing data. By closely observing Fig. 5 the difference between the HOG representation of a pothole and non-pothole images is clear. Table 1 shows the performance of proposed pothole detection scheme. Proposed scheme achieved the accuracy of 90% with precision and recall of 86.5 % and 94.1 % respectively. The proposed scheme has successfully labeled the images with one or more potholes as well as the non-pothole images.



(a) Sample Images from the Testing Data

(b) HOG Representation of Images in (a)

Fig. 5. HOG Feature Extraction Results

Table 1: Performance of Pavement Image Classification

Classification Evaluation Parameter	Values/Measure
True Positives (TP)	32
False Positives (FP)	5
True Negatives (TN)	31
False Negatives (FN)	2
Accuracy	**90%**
Precision	**86.5%**
Recall	**94.1%**

The images labeled by the classifier as pothole images are forwarded to the localization phase for the localization of the pothole (s) in the image. As mentioned in section II, normalized graph cut segmentation with selected number of cuts and a certain threshold for the mean is employed for the localization of pothole (s). Fig. 6 shows the results of applying normalized graph cut segmentation and the refined potholes region for the given images having one or more potholes. As far as accuracy of pothole localization is concerned, scheme resulted in 100 % accuracy with respect to the spatial occurrences of the potholes. Whereas for the in-depth area-based comparison to the ground truth data, 72.3% images resulted in 100 % accurate localization of potholes. In remaining 27.7 % images potholes are localized accurately but they contain false positive and false negative regions in the neighborhood of the actual pothole as well. Fig. 7 shows the potholes images with some false positive and false negative areas. In such 27.7 % images, 18.5 % and 9.2 % images contained false positive and false negative areas respectively.

In comparison to the existing work on the same dataset, proposed technique proved to be much better due to following reasons. First, the proposed scheme has high accuracy (90%), precision (86.5%) and recall (94.1%) as compared to the 85.9%, 81.6% and 86.1% respectively in the work presented in [5]. Second, the pothole localization has been improved now by indicating a pothole through its contour. Third, the pothole localization phase will only invoked when an image declared as pothole image, which made this scheme computationally efficient by ignoring all non-pothole images in localization phase. Average processing time for one pothole image is 0.673 seconds whereas it will be reduced 30% in case of non-pothole image.

IV. CONCLUSION AND FUTURE WORK

A hierarchical approach is presented for the visual analysis of pavement images to be labeled as a pothole or non-pothole image as well as the localization of the pothole in the detected image. HOG features and Normalized cut segmentation proved to be robust for the identification of pothole images. Proposed approach is low-cost, computationally efficient and workable without assumptions of visual and shape appearance of the pothole. The proposed scheme can be utilized by the highway authorities for repair and maintenance of the roads as well as geo-tagging to inform the drivers about road condition.

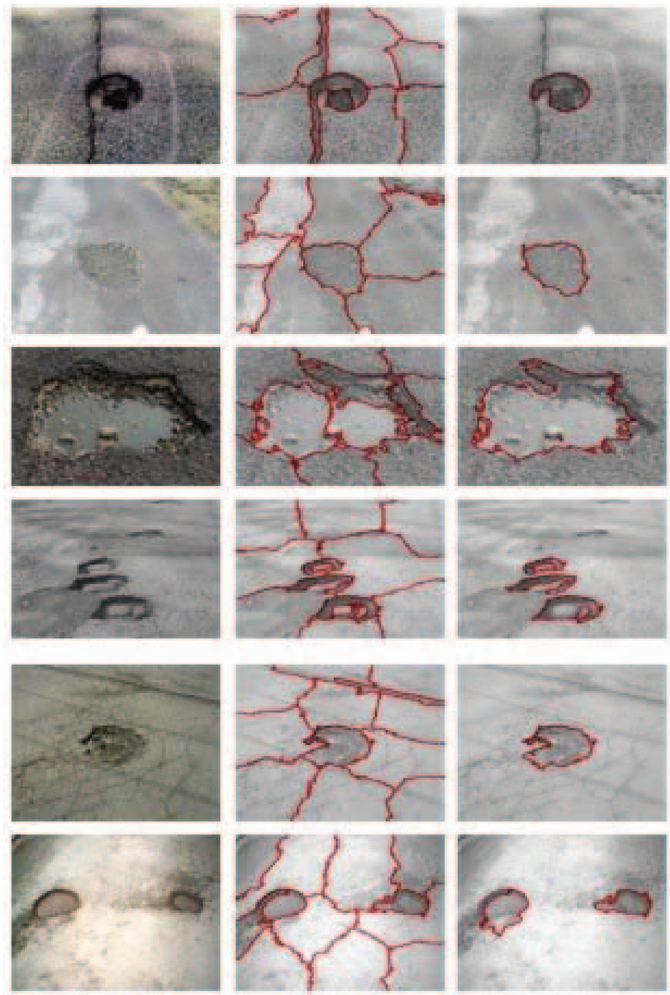


Fig. 6. Pothole Images with Normalized Graph Cut Segmentation and Localized Pothole Regions in the Images

In future, a bottom-up approach with more robust features can be investigated for the defect analysis in the asphalt pavement images. Distresses other than potholes will be visually analyzed and detected using structural features and classifiers. Implementation of the proposed scheme in real-time environment on pavement videos is also pipelined.

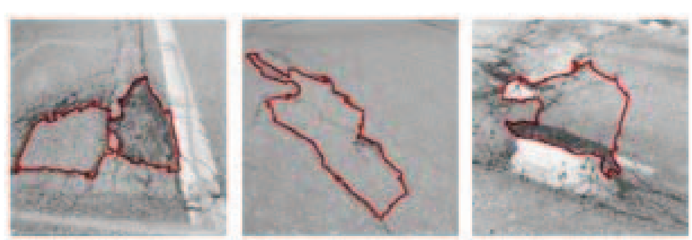


Fig. 7. False Positive and False Negative Areas Examples

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