Road Anomalies Detection Using Basic Morphological Algorithms

Dalia Danilescu, Alexandru Lodin, Lăcrimioara Grama, Corneliu Rusu
Signal Processing Group, Basis of Electronics Department
Faculty of Electronics, Telecommunications and Information Technology, Technical University of Cluj-Napoca
Cluj-Napoca, Romania
{dalia.danilescu, alexandru.lodin}@gmail.com; {Lacrimioara.Grama, Corneliu.Rusu}@bel.utcluj.ro

***Abstract*—In this paper some approaches for pothole detection of roads, using morphological algorithms, are recalled and tested. For road anomalies detection, one of the key elements is the pavement pothole information. Any algorithm for pothole detection has certain advantages and limitations as well, due to the real world environment, which is highly unstructured and dynamic. For road segmentation, the road anomalies detection algorithm based on skeletonization is used.**

***Keywords*—morphological algorithm; image and video processing; road anomalies detection**

I. Introduction

There is a large interest in the automatic road detection in the last years. The costs of the road maintenance have risen considerably. The damaged pavement is increasing in some areas due to the climate change – heavy rains and snows, inefficient methods to drain the water for the roads, and of the increasing traffic as well.

One of the key elements for road anomalies detection is based on the pavement pothole information. A pothole is a type of failure in the pavement surface, caused by factors like erosion, weather, traffic, etc. [1].

When such anomalies are accumulated in the transportation system, they may create some major problems as: accidents, traffic coagulations, inefficient engine functioning, damage to the vehicles that use those roads with potholes, etc. These problems have a large impact on the economy and on the day to day life of people. If the roads are verified timely, potholes can be localized and filled up. In this way the traffic system can be improved.

The detection of potholes on roads by the aid of intelligent systems is a well-studied problem [1]. The identification, and hence the avoidance of potholes, may reduce the fuel consumption, wear-tear, and maintenance cost of vehicles.

By avoiding potholes, road safety increases and, indirectly the total travel time can be decreased, in some situations. Some solutions for the above mention problem can be: establishing pothole hotlines, holding contests to report particularly bad potholes, and asking people to contribute with potholes' images.

Another important aspect for maintaining smoothly the traffic flow is given by the road maintenance [2]. Most of the developed countries are faced with high maintenance costs on the aging transportation highways. Road maintenance normally excludes upgrading and strengthening of the road elements. If upgrading and strengthening of the road elements are considered to be effective as long term solutions, they can be included in road maintenance phase. The maintenance can be classified as emergency, remedial (routine or recurrent), and preventive (periodic). The road maintenance must be planned, managed, designed and executed. Planning and managements steps are done by means of maintenance management systems and procedures [2].

In real time practice, for collecting pavement images and video data, sophisticated digital inspection vehicles are used. The problem is that the estimation of damage is reviewed manually by technicians, not automatically, being a time-consuming and expensive task. If the pavement assessment method can be automated, these costs can be reduced significantly. Computer vision and image processing techniques may be used not only for data collection but for processing data as well [3]. Moreover, by the aid of automation the human intervention could be reduced to minimum and the results produced would be more precise and accurate; in this way the factor of subjectivity and the level of experience will be eliminated.

This work focuses on identifying potholes on pavement images and video. For this, some road anomalies detection algorithms were studied and applied to a collection of 2D images and video data.

In order to simulate a real scenario, images are collected by a camera embedded in a car; we do not use pictures taken from a specific road segment. Before applying a road anomalies detection algorithm, a road segmentation algorithm is applied to image and video collection data. The road segmentation algorithm starts by using the street tracks. This approach is not robust enough because there are some roads without tracks or with eroded center lines and sidelines. To outrun these drawbacks the adopted method performs a segmentation using a conditioned watershed algorithm [4] with pre-defined markers, having at the center the road position. The main techniques for the road detection algorithm are based on mathematical morphology operations [5].

The paper is organized as follows: in Section II the related work is presented and in Section III the road anomalies detection algorithm is described. Some test results are illustrated in Section IV. In Section V conclusions are dragged.

II. Related Work

As a background for this research several studies are outlined in the road anomalies (potholes and crack) detection.

The study in [6] aimed to detect a variety of road-related objects such as lanes, road signs and potholes. The paper states that a pothole is normally characterized by a distinctive black color in the road; this can be the predominant characteristic to detect a pothole. For a successfully segmentation, in order to highlight the pothole area, white and black thresholds were applied to the test image.

The conclusion of the study presented in [6] was that the algorithm does not give the expected results; also, it is segmented a lot of undesirable areas within an image. A better filtering method is needed in order to improve the accuracy of the approach. No machine learning techniques were applied to detect the anomalies. The main detection and classification mechanism used was a system incorporating image processing algorithms.

The method presented in [7] for detecting potholes uses the segmentation of a road based on its defect and non-defect regions. Similarly to the previous approach, it uses a histogram shape-based thresholding algorithm for images. A pothole is detected in a defect region by the use of morphological thinning and elliptic regression. Morphological thinning is an algorithm used on binary images to separate foreground pixels from the background ones [8].

The paper assumes that a pothole is elliptically shaped, thus an elliptic regression algorithm is implemented in order to determine how well the collection of data points (pixels) fits an elliptical shape. All of the images processed by the algorithm were obtained by placing a high-speed camera on a robot. This simulates camera placement on the back of a moving vehicle such that the camera would be tilted towards the road surface. Images were processed in two stages.

In the first stage the frames with defect region were identified, using real time processing. To the second stage only the frames with defects are passed; for a more complex pothole detection algorithm is used. 50 pothole images were used for training the system and 70 images for testing it. The system precision reported is 81.6%. The used images were mostly acquired via Google Images; these were taken by different people, with different cameras, at a variety of angles to the road surface. Some of the photos were taken up close to the potholes whilst others were not.

Once a pothole is detected, it can be tracked such that the same pothole in subsequent frames is only counted as a single pothole occurrence. This is useful when it is necessary to accurately determine the number of detected potholes. In [9] a method for tracking the potholes between frames is discussed. This paper focuses on warning drivers about potholes, thus it is only necessary to detect whether a section of road has potholes or not.

Pothole detection via spectral clustering is another option, as presented in [10]. The work in [10] is based on Koch and Brilakis research [7]. The thresholding algorithm was slightly modified: it uses Otsu's image thresholding; the correct threshold value necessary per frame is determined automatically, using internal algorithms [11]. The method was tested on images obtained from Google.

It was previously stated that it is possible to exploit a variety of physical properties in order to detect potholes. Such an attempt is presented in [12]: various InfraRed sensors built into a Microsoft Kinect [13] were attached to the back of a vehicle. Initial results were given but the utilization of the system in broad daylight is problematic due to the overwhelming presence of InfraRed, radiated by the sun as was demonstrated by Drexel Autonomous Systems Laboratory (2013).

III. Methodology Description

A. 2D Image and Video Data Collection

2D signals used are still images and video frames purchased on a road characterized by serious anomalies (potholes and cracks) which is in a village situated in the county of Sibiu. To acquire images, a GoPro camera mounted outside on the back of the car was used. It acquired still images and video frames, respectively. For the latter, the purchase was made during car movement. Video frames were extracted. An individual frame was considered to be an image which was subsequently processed.

The resolution of a still image or of an individual video frame has been selected to ensure compatibility and minimum processing time. The camera resolution was 1920x1080, 30p, 16.9. The exposure conditions and some of the data in the acquisition are shown in Table I.

B. Algorithms

The proposed method for automatic activities is the road potholes and cracks (anomalies) detection algorithm.

In a preliminary work the watershed segmentation was applied to the collection data [14]. The aim of the pre-processing algorithm was to extract only the road surface and to remove the height parts (such as sky, natural environment) and the buildings, sidewalk from each side of the road.

TABLE I. The Exposure and Acquisition Conditions of Video Data and Still Images

Exposure condition	*Video data*	*Still images*
Height	106 cm	106 cm
Distance	5 km	5 km
Speed	10 km/h	0 km/h

Using the collected images and video data mentioned at the exposure condition from Table I, the methodology to detect road potholes presents the next steps:

- The original color image is cropped based on the road extraction algorithm (the interest region with potholes and cracks);
- Noise removal in the original image using a Gaussian LPF (low pass filter) [11];
- Simplification of the original image by binarization using Otsu's algorithm [14]
- The skeletonization morphological operation is applied.

The initial image is acquired using the exposure conditions specified in Table I. The image is cropped to 50% of height; this removes the top parts of the image, i.e. sky and background natural environment. Also, 40 % of the width is cut by the removal of 20% on each side.

Then, the image is converted to gray scale, after which the fast Fourier transform is applied. Next, the convolution with the Gaussian LPF is computed.

For removing noise, the Euclidean distance from the origin and a cut-off radius is evaluated, to remove high frequencies. The convolution performed is expressed as in (1) [15]:

$$H(u,v) = e^{-\frac{d^2(u,v)}{2d_0^2}} \quad (1)$$

where d_0 is the cut-off frequency, $d(u, v)$ is the Euclidian distance from origin, and u and v are the frequency variables. As the smoothing operator forms the convolution with the Gaussian LPF, the output will be less blurry compared to the cases when an ideal LPF or a Butterworth LPF are used [15].

The next step consists in applying the Otsu's method [16] to obtain the cell pixels by thresholding the image. Otsu's algorithm searches for a threshold value that maximizes the variance between the two groups: foreground and background, so that the threshold value can better segment the foreground from the background.

The thinning operation is applied several times such that only the connected pixels are retained. This process is known as skeletonization [15]. This is a form of erosion through which many pixels in the foreground are removed and only the connected pixels are retained. Thinning [15] is the opposite of thickening:

$$\text{Thinning}(I) = I - H \quad (2)$$

Thickening [15] the image I with the structure S is expressed in (3):

$$\text{Thickening}(I) = I \cup H \quad (3)$$

where H represents the hit-or-miss on image I with S. Thinning and thickening operation can be applied repeatedly.

After skeletonization the foreground pixels are shrunken and only the connected pixels survive. For this reason, skeletonization is often used in measuring the length of objects. Once the foreground pixels are shrunk to one pixel width, the length of the object is approximated as the number of pixels after skeletonization.

IV. Test Results

In order to prove the capability of the proposed method, a prototype version was developed. The programming language of choice was Phyton, mainly for its design philosophy which emphasizes code readability and also for the large number of scientific modules and tools available.

The prototype version of the method relies heavily on a few well known image processing libraries: OpenCV (Open Source Computer vision), SciPy (Scientifiv Python) and SciKit (image processing toolkit for SciPy).

The required input of the method, illustrated in Fig. 1, represents the original raw image collected with the GoPro camera. The first processing step consists of reducing the image area of interest by means of cropping the top, left and right side sequentially.

After obtaining the area of interest, as in Fig. 2, the next processing step involves the use of a smoothing operator such as the Gaussian one. For our experiments, we have used a Gaussian LPF with a convolution kernel of size 5. The goal here was to remove the unwanted details and noise.

Observing that the resulting image, depicted in Fig. 3, contains two classes of pixels following bi-modal histogram, we have realized that an automatic clustering-based image thresholding is most suitable in this case. Therefore we have used the Otsu's method for binarization. The result is displayed in Fig. 4.

Fig. 1. Input image.

Fig. 2. Cropped image.

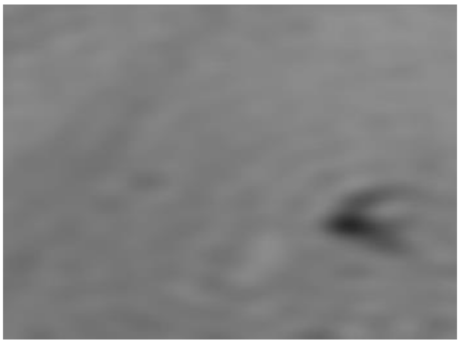

Fig. 3. Blurred image.

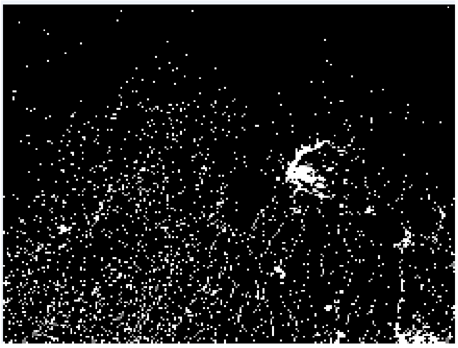

Fig. 4. Image obtained after the Otsu's method is applied.

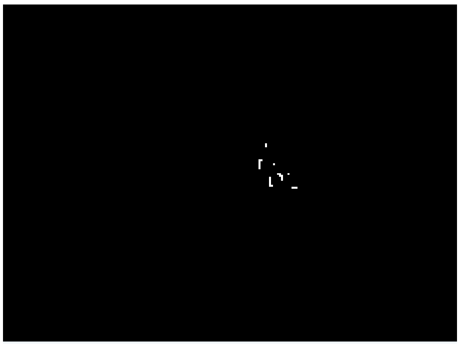

Fig. 5. Image obtained after the Otsu's method is applied.

As the final step, we have used the morphological algorithm called skeletonization, available with the SciKit morphology module. This algorithm consists of making successive passes of the input image, with each such pass, border pixels are identified and removed on the condition that they do not break the connectivity of the corresponding object. In out particular case, the result of skeletonization process can be observed in Fig 5.

V. Conclusions

For road anomalies detection based on skeletonization, one of the key elements is the pavement pothole information. Any algorithm for pothole detection has certain advantages and limitations as well, due to the real world environment, which is highly unstructured and dynamic.

The aim of this research was to study and test an efficient method to detect road anomalies. Some approaches for pothole detection of roads, using morphological algorithms, were recalled.

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