Morphological Image Processing for Road Anomalies Detection Using 2D Images and Video Data

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Abstract—in Romania the damaged pavement is increasing due to climate change: heavy rains and snow, the poor or inexistent methods to drain water from the roads and because of the increasing traffic as well. One type of pavement distress is potholes. As time progresses, the severity of these distresses increases and consequently, ride quality is adversely affected. In order to solve this problem researches are performed for developing a technology which can detect and recognize potholes based on 2D images and video data. In this paper, a vision based algorithm for damaged pavement detection is proposed using morphological image processing which may result into a potential direction of developing a detection method to efficiently and accurately detect potholes.

Keywords—potholes; morphological image processing; 2D image; video data; vision-based approach

1. INTRODUCTION

A pothole is defined as a type of failure in the pavement surface, [1] caused by the presence of water in the underlying soil structure and the presence of traffic passing over the affected area. Potholes can generate damages as follows:

1) flat tire and damage at the wheel system;
2) impact followed by damage of vehicles;
3) sudden stops which cause suspension and steering problems;
4) vehicle collision and accidents.

The damaged pavement, like potholes is affected and also is increasing because of the two major causes: water and traffic. The climate change has also a serious contribution. In regions subject to freezing and thawing, frost heaving can break the pavement and can create openings for water to enter. As mentioned in [2] spring thaw of pavements accelerates this process when thawing of upper portions of the soil structure in a pavement cannot drain past still frozen lower layers, thus saturating the supporting soil and weakening it.

The inland transport system hold a great importance in modern life, having an impact on citizens lives, to the economy system. All types of automobiles, such as motorcycles, cars, trucks, buses etc., are one of the most important modes of transportation. However, to this mode of transportation to work properly, roads are required, whereas the road conditions are directly related to the trips in both qualities, as comfort and safety, but also to the performance (travel more in less time). These roads often consist of asphalt, concrete, or composite pavements.

Pothole detection is one of the important tasks for the proper planning of repairs and rehabilitation of the asphalt-surfaced pavements. Existing methods for detection and estimation of potholes usually use sophisticated equipment and impose computationally intensive tasks. In current practice, sophisticated digital inspection vehicles are used to collect pavement images and video data, but the estimation of damage is reviewed manually by technicians. Thus, it is a time-consuming and costly task. Since it depends on worker's precision and experience, it is usually more subjective than objective.

The main objection of this research is to test and implement a series of algorithms to achieve an improvement in pothole detection based on image processing leading to the relief work done by the technician who uses the machine. In order to monitor the roads condition, several road network maintenance programs have been established, assessing roads condition [3]. To cite two cases, there is the Long-Term Pavement Performance program in United States, concerned with data collection, storage and analysis of the United States and Canada road network [4], and a Google® initiative in Poland on mapping potholes, using the mobile devices accelerometer to detect shocks induced by potholes while traveling by automobile. The collected data is sent to Google, which displays this additional information on Google Maps.

The collected road images used in vision-based approaches are commonly assessed by technicians without computational aid, a time-consuming and costly task that may be influenced by subjectivity and personal experience. There are already some researches using automated systems for road problems detection, which have the main objective of reduce the number of pictures, leaving only the critical images for technical evaluation [4].

Having almost the same goal, this paper discusses an approach using morphological image processing for road anomalies, potholes detection. In order to present the developed algorithm, this paper was organized as follows. In Section 2 some related work is presented. The road segmentation algorithm is described in Section 3. Some test results are shown in Section 4. Finally Section 5 contains the conclusions.

2. RELATED WORK

Current research efforts in automating the detection of potholes [4] can be divided in three types of methods:

- 3D reconstruction-based;
- vibration-based;
- vision- based;

In the first approach, the laser scanning (used to generate 3D point clouds) and stereo-vision, seems to be the most used techniques. However, this kind of approach is costly and requires high computation efforts, hampering its use in real-time approaches.

The second uses primarily accelerometers and microphone to detect the vibrations based on the vehicle mechanical responses [5]. This technique requires small data storage and it can be real-time processed. However, one needs to pass through the road anomalies in order to detect it, i.e. one have to damage his automobile on a pothole to generate the required data to the detection.

In the third approach, 2D vision images and video data are used to segment the road damages from the regular roads. This method however, is affected by the illumination level, shadows, climatic weather, car obstruction and overall image quality.

For the visual-based approach, in [4] the authors have presented an algorithm for automating the process of pothole detection using visual pavement data. This method by Koch and Brilakis has three main principles:

A. the darker shadows than the environment (road) are considered potholes,
B. from a perspective view potholes are considered to have an elliptical shape,
C. the inside pothole's texture is considered to be coarser and grainer than the normal pavement.

Based on above observations, the proposed model includes three major steps:

1) image segmentation,
2) shape extraction,
3) texture extraction and comparison.

As mentioned in [4] the collected image is transformed into a grey-scale, then a 5 by 5 median filter is used to reduce noise, and a triangle algorithm from [6] is applied over the image histogram in order to segment the road anomalies from normal road (based on principle A), creating a binary image. This image is evaluated based on its shapes and sizes of the segmented regions. Based on the major axis length, central position and orientation angle, each connected component is evaluated as a partial pothole or entire pothole candidate. When partial potholes are discovered, the morphological thinning is used to shrink the shade region to a skeleton, then an elliptic regression results in the probable entire pothole region (according to the principle B). The texture inside a pothole candidate is assessed through standard deviation from inside pothole candidate texture and normal road texture.

In order to meet the third visual characteristic of potholes, the surface texture inside a pothole candidate has to be described and compared with the texture of the surrounding region. This step is essential in order to distinguish between false candidates (small repair patches, spot shadows and discoloration) and true potholes.

In [4] for testing the algorithm, Koch and Brilakis used a collection of 70 road pictures taken with robot aid, simulating an ordinary passenger vehicle equipped with a high-speed camera. The created picture database had 30 distress photos which contained one or two potholes each. For this set of images, the algorithm accuracy was 85.8%, its precision was 81.6% and its recall 86.1%.

However, the method by Koch and Brilakis was limited to single frames and therefore cannot determine the magnitude of potholes in the frame of video-based pavement assessment. In order to complement and improve the previous method, Koch et al. presented an enhanced pothole-recognition method which updates the texture signature for intact pavement regions and utilize vision tracking to track detected potholes over a sequence of frames [7]. The proposed method from [7] was implemented in MATLAB and tested on 39 pavement video containing 10,180 frames. The resulting total recognition precision and recall were 75% and 84%, respectively. Consequently, compared with the previous method, the texture-comparison performance was increased by 53%, and the computation time was reduced by 57%. They assumed that only one pothole enters the viewport at a time, and therefore additional work is needed for considering multiple potholes in the viewport.

Recently, Buza et al. proposed a new unsupervised vision-based method which does not require expensive equipment, additional filtering and training phase [8]. Their method deploys image processing and spectral clustering for identification and rough estimation of potholes. The proposed method is divided into three steps:

- image segmentation,
- shape extraction using spectral clustering,
- identification and extraction.

The proposed method [8] was implemented in MATLAB and tested on 50 pothole images which were selected from Google image collection. The accuracy for estimation of a pothole surface area was about 81%.

Therefore, this method can be used for rough estimation for repairs and rehabilitation of pavements.

Although there are several visual-based approaches, most of them use pictures taken from good perspectives that, most of times, have its focus on the anomalies; this, however, might be difficult to do in real case scenarios. Perhaps the plainest method to photograph roads for analysis is an approach like Google® did in order to collect data for its application Google® Street View: use of a camera embedded in a car that whilst travels by the roads, also takes pictures of it. The algorithm presented in this paper was conceived aiming the use of pictures in a visual-based approach.

2.1. 2D Image and Video data collection

The collected 2D images and video data were taken from a locality situated in the Sibiu county were the roads have serious anomalies. To collect video data, a camera was mounted on the car. Frames of the video are extracted and the individual frame is considered as an image which is further processed. Resolution of the plain road image and pothole image has been kept the same to ensure compatibility and minimum processing time. For collecting video data of potholes a resolution camera of (1920*1080, 30p, 16.9) was mounted in the back of the car (outside on the trunk), and it recorded the road surface from the back during movement.

Table 1 The exposure condition of video data and still images in this study

The exposure condition of video data and still images		
Exposure condition	***Video data***	***Still images***
Height	106Cm	106Cm
Distance	5Km	5Km
Speed	10Km/h	0Km/h

2.2. Algorithms

A morphological visual-based algorithm for detection of the damaged road such as potholes and cracks is proposed in order to automate some activities in the paved asphalt road anomalies detection. In this approach, a real scenario was simulated, where 2D images and video data are collected by a camera embedded in a car, instead of using pictures taken from a specific road segment. For this reason, two algorithms are needed. In this paper is presented only the first one, for the road segmentation. The second one is for road potholes and cracks (anomalies) detection which is a working in progress study and which will be presented in future papers.

3. ROAD SEGMENTATION ALGORITHM

For the segmentation of roads was used the street tracks, however this approach would not be robust enough, since there are some roads without or with eroded center lines and sidelined. The applied approach was to perform a segmentation based on the Watershed algorithm [9] with the predefined markers.

To perform watershed segmentation, a grayscale image is considered. The grayscale values of the image represent the peaks and valleys of the topographic terrain of the image [9]. The watershed algorithm can be explained as follows: all the points in a region where if a drop of water was placed will settle to the absolute minimum are known as the catchment basin of that minimum or watershed. If water is supplied at a uniform rate from the absolute minimum in an object, as water fills up the object, at some point water will overflow into other objects. Dams are constructed to stop water from overflowing into other objects/regions. The dams are watershed segmentation lines. The watershed segmentation lines are edges to separate one object from another [9].

Based on [9], let us look at how the dams are constructed. For simplicity, let us assume that are two regions. Let R_1 and R_2 to be two regions and let C_1 and C_2 be the corresponding catchment basins. For each time step, the regions that constitute the catchment basins are increased. This can be achieved by dilating the regions with a structuring element of size 3-by-3. If C_1 and C_2 become one connected region in the time step *n*, then at the time step *n-1* the regions C_1 and C_2 were disconnected. The dams of the watershed lines can be obtained by taking the difference of images at time steps *n* and *n-1*.

In 1992, F. Meyer proposed an algorithm to segment color images [10]. Internally, the watershed function uses Meyer's flooding algorithm to perform watershed segmentation.

First of all, the color image is converted to a grayscale image. Later the Otsu's method [11] is applied for thresholding the image to obtain the cell pixels.

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.

Let *L* be the number of intensities in the image. For an 8-bit image:

$$L = 2^8 = 256 \tag{1}$$

For a threshold value, *t* the probabilities, p_i of each intensity is calculated. Then the probability of the background pixels is given by:

$$P_b(t) = \sum_{i=0}^{t} p_i \tag{2}$$

Then the probability of foreground pixels is given by:

$$P_f(t) = \sum_{i=t+1}^{L-1} p_i \quad (3)$$

Let:

$$m_b = \sum_{i=0}^{t} ip_i \,,\; m_f = \sum_{i=t+1}^{L-1} ip_i \text{ and } m = \sum_{i=0}^{L-1} ip_i \quad (4)$$

represent the average intensities of the background, the foreground and the whole image respectively. The v_b, v_f and v represent the variance of the background, foreground and the whole image respectively.

Then the variance within the groups is given by Equation (5) and the variance in between the groups is given by Equation (6).

$$v_{(within)} = P_b(t)v_b + P_f(t)v_f \quad (5)$$

$$v_{(without)} = v - v_{(within)} = P_bP_f(m_b - m_f)^2 \quad (6)$$

For different threshold values this process of finding variance within the groups and variance between the groups is repeated. The threshold value that maximizes the variance between the groups or minimizes the variance within the group is considered Otsu's threshold. All pixel values with intensities less than the threshold value are assigned a value of zero and all pixel values with intensities greater than the threshold value are assigned a value of one.

The next operation applied, is erosion. Erosion is used to shrink objects in an image by removing pixels from the boundary of that object. The erosion of an image I and with a structuring element S is denoted as: $I\ \theta\ S$ [9]. Distance transform operation is applied after erosion in order to create an image where every pixel contains the value of the distance between itself and the nearest background pixel. The thresholding is done to obtain the pixels that are farthest away from the background pixels and are guaranteed to be foreground pixels.

All the connected pixels in region are given a value in the process known as labeling [9]. The labeled image is used as a marker image. Labeling is used to identify different objects in an image. For each region in the marker image, its neighboring pixels are placed in a ranked list according to their grey levels. The pixel with the highest rank (highest grey level) is compared with the labeled region. If the pixels in the labeled region have same gray level as the given pixel, then the pixel is included in the labeled region. Then a new ranked list with the neighbors is formed. This step contributes towards the growing of the labeled region. The above step is repeated until there are no elements in the list.

4. TEST RESULTS

A prototype version of the algorithm was implemented using the morphological algorithms. The various Python statements leading to the watershed function create the marker image.

The image in Fig. 1 represents the original image of a county road from Sibiu County.

Fig. 1. Input (original) image of a county road

Then the image is read and thresholded in order to obtain the foreground pixels (Fig. 2.)

Fig. 2. Thresholded image using Otsu's algorithm

The image is converted to a grey-scale image before thresholding. Fig. 3 shows how the image is eroded to ensure that guaranteed foreground pixels are obtained.

Fig. 3. Image after erosion

Next the distance transform is applied (Fig. 4) and the corresponding thresholding which ensures the guaranteed foreground pixel image (i.e. marker image) is obtained.

Fig 4. Distance transform image

The marker image is used in watershed to obtain the image shown in Fig. 5. The inputs for the watershed function are input image as a color image and a marker image.

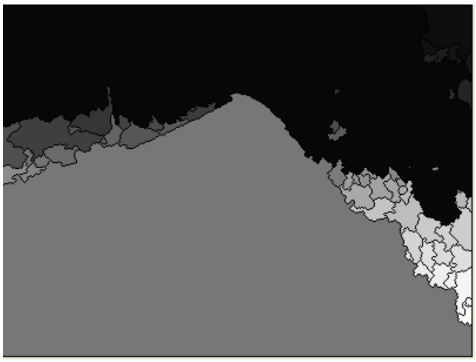

Fig. 5. Output of the watershed

For video data the inputs are based on the extracted video frames which are saved as images. This function is available in the OpenCV module for Python as well.

5. CONCLUSION

The purpose of this paper is to show an efficient system and method to detect road anomalies, starting with the watershed algorithm which is applied for road segmentation. The images and video data were taken by a go pro camera embedded in a car. The proposed algorithm for the road detection using watershed algorithm has shown good results.

For further studies, the use of different parameters, such as watershed markers could and might be evaluated and also the RGB road should be obtained again having a white background. The second part of the future work will consist of the road anomalies detection algorithm as well.

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