PATCHES DETECTION ON ROADS USING MACHINE-LEARNING TECHNIQUES

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Abstract- *The primary form of transportation is thought to be roads.But due to this heavy use of roads and environmental factors, roads need a scheduled maintenance. This maintenance is frequently neglected since it is impossible to watch over every location or just out of ignorance. This leads to the formation of potholes or patches which causes unwanted traffics and the majority of accidents. Project discusses about the detection of potholes or patches using camera. Image processing techniques have been used which informs the officials in a timely manner using email system, thus keeping manual labour to the minimum.The suggested system has been implemented using the Open CV library in a Windows environment to test its performance. Simple image processing techniques like canny edge and contour detection with Hough transform is used for effective patches detection.*

Keywords- Pathole detection, computer vision, disparity map,dynamic programming, road surface modeling, golden section search, surface normal.

I. INTRODUCTION

Potholes or Patches are bowl-shaped openings on the road that can be up to 10 inches in depth and are caused by the wear-and-tear and weathering of the road. They emerge the top layer of the road, the asphalt, has worn away by lorry traffic and exposing the concrete base. Once a pothole is formed, its depth can grow to several inches, with rainwater accelerating the process, making one of the top causes of car accidents. Potholes are not only the main cause of car accidents, but also can be fatal to motorcycles. Potholes on road are especially dangerous for drivers when cruising it in high speed. At high speed, the driver can hardly see potholes on road surface. Moreover, if the car passes through potholes at high speed, the impact may rupture car tires. Even though drivers may see the pothole before they pass it, it is usually too late for drivers to react to the pothole. Any sharp turn or suddenly brake may cause car rollover or rear- end. From above reasons, it a system to detect potholes on roads while driving and the proposed system will produce the 3-dimensional information of potholes. Introduction to Currently, the main methods for detecting potholes still rely on public reporting through hotlines or websites. However, this reporting usually lacks accurate information of the dimensional and location of potholes. Moreover, this information is usually out of date as well. A method to detect potholes on road has been reported in a real- time 3D scanning system for pavement distortion inspection which uses high-speed 3D transverse scanning techniques. However, the high-speed 3D transverse scanning equipment is too expensive. Regions corresponding to potholes are represented in a matrix of square tiles and the estimated shape of the pothole is determined.However, the 2D vision-based solution can work only under uniform lighting conditions and cannot obtain the exact depth of potholes. To remove the limitations of the above approaches, we propose a detection method based on computer stereo vision, which provides 3-dimensional measurements. Therefore, the geometric features of potholes can be determined easily based on computer vision techniques. Before convert the image coordinates to the world coordinates, some preparation work needs to be done. Image pairs of road surface should be undistorted and also rectified. In undistorted images lens distortion has been removed. Rectification refers to projecting image pairs onto a common image plane, respectively. The rectified and undistorted image pairs are used to calculate the disparity map using the stereo camera parameters obtained before with the semi-global matching algorithm provided in OpenCV.

II.EXISTING SYSTEM

In an existing system a detection which starts with noise removal, followed by adjustment of brightness and simplification of video by binarization. Then, noise removal is applied to binarized image. After noise removal, the process of extraction of outlines of the segmented objects is carried out. Extraction is followed by selection and square zoning for objects. After all these processes, desired pothole area information's is returned. And another pothole detection system which is divided in to three subsystems. First is sensing subsystem which senses the potholes encountered by it, by using accelerometer or by camera which scans the roads. Both are mounted on the car. Then a communication subsystem which transfers the information between Wi-Fi access point and mobile node. Access point broadcasts the data about potholes in its areas. In the existing system, the

pothole is detected using the accelerometer sensor in smartphone. This system is not automotive in nature. The complaints if needed to be posted or to be informed to any governmental authority it will be done only with human intervention. This process may not provide the complete efficiency as many people may ignore the issue and will not post them. Even if people send the complaint to an admin many patches image may be repeated and thus it may cause a huge confusion. In this case, if prioritization
has been done then it would be an optimized way to collect the frequent places that are being affected by potholes. Though potholes are being detected there are many factors which lead to life disorders such as accidents which happens due to obstacles. This cannot be avoided in the existing system.

III.PROPOSED SYSTEM

Video has been captured using a camera. Frames of the video are extracted, and the individual frame is considered as an image which is to be further processed. The image is firstly blurred using averaging then with Gaussian filter and lastly with median blur to remove unwanted noise from the image. To achieve the exact accurate edge detection from a depth image we have modified the process using morphological operations. These operations are generally a collection of non-linear operations carried out comparatively on the ordering of pixels without affecting their numerical values. The key operators include for morphological operations are erosion and dilation.After performing blurring procedures and two cycles of dilation, we employed erosion. Pothole detection is utilizing canny edge detection technique. The detection technique is a multi-stage method to detect the wide range of edges in images. Images define the world, each image has its own story, it has a lot of crucial information that can be useful in many ways. This information can be obtained with the help of the techniques known as Image Processing.An image can be represented as a 2D function F (x, y) where x,y are spatial coordinates. The amplitude of F at a particular value of x, y is known as the intensity of an image at that point. If x, y and the amplitude value is finite then we call it a digital image. It is an array of pixels arranged in columns and rows. Pixels are the elements of an image that contains information about intensity and color. An image can also be represented in 3D where x, y and z become spatial coordinates. Pixels are arranged in the form of a matrix. This is known as an RGB image.

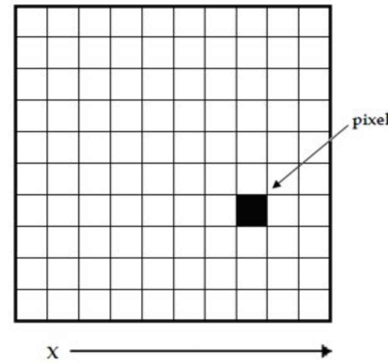

Figure 3.3 A digital image is a 2D array of pixels

Architecture Diagram

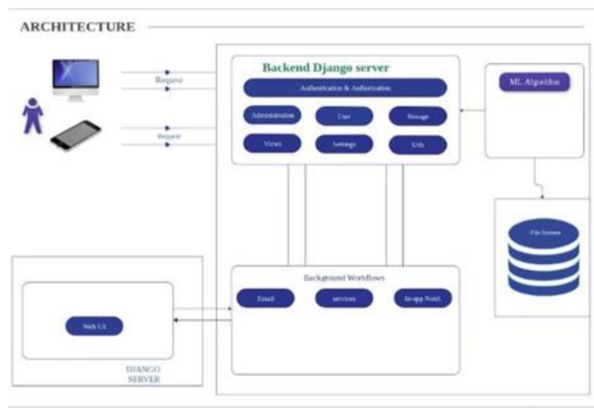

Fig.[1] Architecture diagram

IV. MODULE

1) Pre-Processing
2) Non-Crack Feature Detection
3) Road Surface Classification
4) Adaptive Road Distress Detection
5) Road Distress Detection

4.1) Pre-Processing

Pre-processing is one of the key steps of the whole distress detection system. The main idea is to ease the cracking detection process by both reducing noise and enhancing the dark linear features (possible cracks). Common pre-processing techniques are based on gray-scale morphological filters image equalization combinations of morphological tools and segmentation methods and median filters. Our approach is based on the assumption that the intensity of crack pixels is darker than the intensity of the pixels around the cracks. Therefore, a peak will show up at the start of the histogram if we choose a small region of interest (ROI) around a fracture location. The procedure can be summarized as follows. Using a sliding window technique, square ROIs with a pre-defined shifted over the image. A specific step is used for shifting the window. The parameter will determine the size of the pre-processing image since each ROI will be represented by only one pixel.Additionally, depending on the step parameter, regions may overlap. The cumulative histogram $M_i=\sum_{j=0}^{i} m_j$ is produced from bin I = 0 to I = 255 for each ROI using the intensity histogram Mi.Once the cumulative number of observations Mi reaches a pre-defined threshold (thpre) we store the current bin value (pout = i). The threshold represents the percentage of pixels with a gray level value lower than pout. The local ROI is then replaced by one pixel (downsampling) with a gray level value equal to the current bin of the histogram (pout).Thus, local regions with crack pixels will be assigned with lower gray level values than regions without crack features.We store the current bin value (pout = I) after the total number of observations Mi hits a predetermined threshold (thpre).The threshold shows the proportion of pixels with a pout -level grey value. Next, one pixel (downsampling) with a grey level value equal to the current bin of the histogram is substituted for the local ROI (pout). The grey level values allocated to local regions with crack pixels will therefore be lower than those to regions without crack characteristics. The identical input parameter will produce two distinct outputs, pout1 and pout2, which are pout1 pout2 and represent the crack and non-crack subregions, respectively.

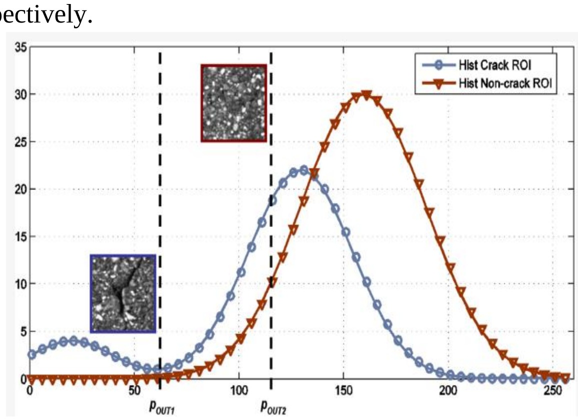

Fig.[2] Crack-related histograms (blue) and non-crack-related histograms (red).

We point out that the pre-processing procedure is based on the sizepre, steppre and thpre three primary factors. Depending on the output (kind of pavement) provided by the classification stage, these parameters will be adjusted. Additionally, it is significant to remember that, depending on the step value, the pre-processed image has a lower resolution than the original one. On the one hand, because the input image is smaller and the noise has been visibly flattened, further processing will be quicker. On the other side, the downsampling process results in the loss of some details.

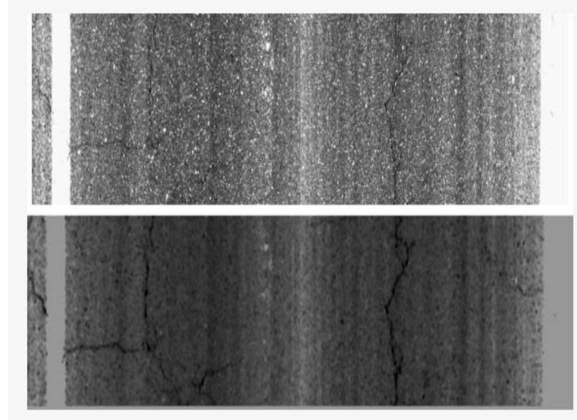

Fig.[3] Original image is in the top row. Lower row: the image after processing.

4.2) Non-Crack Feature Detection

The majority of distress detection systems exhibit excellent sensitivity to both crack and non-crack features, leading to a very low number of false negatives. But when these systems have to cope with joints, patches, white painting, sealed cracks, etc., a lot of reported cracking is typically obtained, leading to a lot of false positive crack reports. A crucial component of assessing the condition of the road surface and a way to spot false positives during fracture detection is the capability to capture non-crack elements on the road surface. In our instance, we construct a particular map with the non-crack qualities of sealed cracks, joints, and white painting. This map can be used to hide the reports of cracking or to narrow down the area of interest where cracks are found.Sealing the cracks is a widely popular method of mending non-critical parts of the road. On pictures, sealed cracks typically appear as broad, black lines (patches), and most detection methods flag the boundaries of the patches as false positives. We employ the pre-processed image to identify sealed cracks, greatly reducing computing costs without sacrificing accuracy. The first step is to apply a simple adaptive grey-level threshold step. Then, contours are found over the eroded (inner contour) and dilated (outer contour) images. Short contours are first filtered out and ignored. The average gray-level values of the pixels corresponding to the inside and outside of both contours are then calculated.Because the pixels corresponding to the inner contour of the sealed fractures would have lower grey-level intensities than the pixels corresponding to the outer contour, this is the basis for our detection algorithm. Because cracks are much thinner than sealed cracks, we cannot absolutely talk about inner and outer contours for cracks. Therefore, thisassumption does not apply to crack features. More particularly, the interior contour of fractures does not leave after the erode operation.

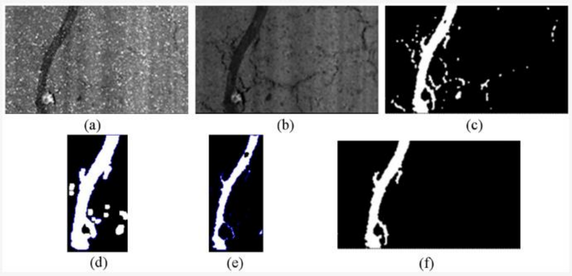

Fig.[4] (A)The initial image; (B) The pre-processed image; (C) The thresholded image; (D) The outer contour following the dilate operator; (E) The inner contour following the erode operation; and (F) The outcome.

It is necessary to quantize the parameter space, p = (ρ, θ), and express it in a 2D accumulation matrix, a, whose elements are initially set to 0. As a result, for each contour point (xiyi) in the image-domain, an element a(ρ, θ) is incremented by 1. In order to speed up the Hough transform's computation, various techniques have been developed. In the coarse-to-fine approach, a multi-dimensional quadtree structure for accumulating is recommended. The many-to-one mapping method is based on the idea that a pair and a triple of points from the original image can be used to uniquely identify a single parameter space point. In this instance, the computation time is reduced by using a limited accumulation matrix.

4.3) Road Surface Classification

Due to the wide variety of road surfaces that can be found in real contexts, a road surface categorization step is required. A monolithic road distress detection system that can deliver decent results with the same parameter settings regardless of the type of pavement is incredibly challenging to create. In order to trigger the road distress detection algorithm with a predefined set of parameters that are ideal for the particular type of pavement, we have built a stage for classifying road surfaces into different groups. Based on the type of material used to construct the roadways, as well as the level of granulation and striation, the number of classes is determined by visual inspection.Granulation in the various pavement types comes in various degrees, with variations in size, grey level, and distribution. On either rougher or smoother surfaces, granulation occurs. Blobs identification could therefore aid in enhancing classification performance. A MSER detection-based system has been put into practise. The MSER technique was initially introduced as a method to address the wide-baseline stereo problem, but it has since been shown to be an effective blob detector due to its invariance to monotonic intensity transformation and ability to identify several scales. An extremal zone is a collection of related elements that keeps their combined intensities below a certain limit. Extremal regions that meet a stability condition are said to be maximally extremal. The original image is then inverted to identify minimal extremal regions, allowing both dark and brilliant blobs to be seen. Only regions that comply with circular shape requirements are taken into consideration since regions are filtered based on their shape. There are two stated blob size ranges. Examples of white and black blobs detection results are shown using the three statistics that are produced for each of the ranges and grey levels: the quantity of blobs, the averaged size, and the total area.

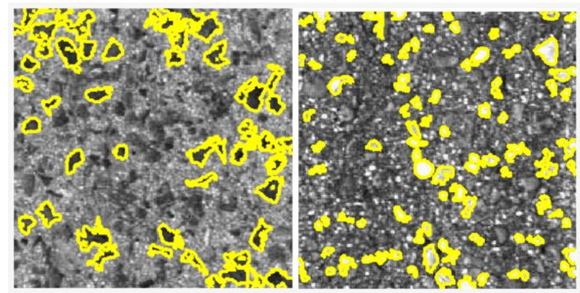

Fig.[5] Results of MSER detection. Left: blobs of darkness. Left: white blobs.

4.4) Adaptive Road Distress Detection

There are a total of 8 parameters in the suggested road distress detection system that need to be adjusted in order to achieve the desired behaviour. The vector Q = {sizepre, steppre, thpre, LW, thSymDiff, KS, thPATH, thSymDiffPATH} that follows describes these parameters. The pre-processing stage is represented by the first three parameters. The remaining variables have to do with the fracture detection technique. With one type of pavement, a particular set of parameters may operate flawlessly, but with another type of pavement surface, it may produce very noisy results. As a result, these parameters must be modified in light of the output the classifier stage produces. To our knowledge, the topic of automatic system parameter optimization has not been addressed in the context of road fracture detection.There is a wealth of literature on numerical techniques for minimising non-linear objective functions. Due to the relatively high number of parameters involved and the significant processing cost associated with a single evaluation of the objective function, such approaches are unsuitable for the current situation. Instead, we used a set of pre-selected photos that match to the 10 classes of pavement to evaluate the system's performance during a manual, supervised method for parameter setting. In this paper, a two-level grid-search technique is especially suggested. In order to ensure that a suitable number of seeds are chosen, the most sensitive parameters are first tuned sizepre, thpre, KS, and thSymDiffPATH are the parameters in question.Only the sets in the first places are evaluated in the second stage, when the remaining parameters are collected, after the results are arranged according to recall. In this manner, the parameter vector Qi, i = 1, ..., 10 that will ultimately be supplied to the road crack detection module is directly selected from the output of the SVM-based classifier. A more complex and automated optimization strategy is outside the purview of this paper and is left for other research.

4.5) Road Distress Detection

The seeds are obtained using a Multiple Directional Non-Minimum Suppression (MDNMS) and a symmetry check outlined for linear feature identification. Non-minimum suppression is a technique for labelling all pixels inside a specific local neighbourhood whose intensity is not minimal as zero. Multiple directional linear windows with angles of 0°, 45°, 90°, and 135° are referred to as this local neighbourhood in this context (see Figure 10(a)). Additional instructions can be used, as suggested. However, just four directions are used because eight directions rather than four have not been shown to significantly improve performance. To prevent repeated local minimums, it is crucial to adjust the length of the linear window (LW) to the size of the images.

$$I_C = I(0,0);\ I_{avg} = \frac{1}{(2N_X+1)(2N_Y+1)} \sum_{i=-N_X}^{N_X} \sum_{j=-N_Y}^{N_Y} I(i,j)$$

$$I_C \leq K_S \cdot I_{avg}$$

For the purpose of detecting seeds, we combine the results of several directional non-minimum suppressions. Additionally, the linear feature's cross-feature gray-level intensity profile at a specific location is roughly regarded as being symmetric around the minimum point (with intensity Imin). Several characteristics are utilised, as shown in, to determine whether a local minimum is present along a linear feature in the image for a specific direction (linear window).

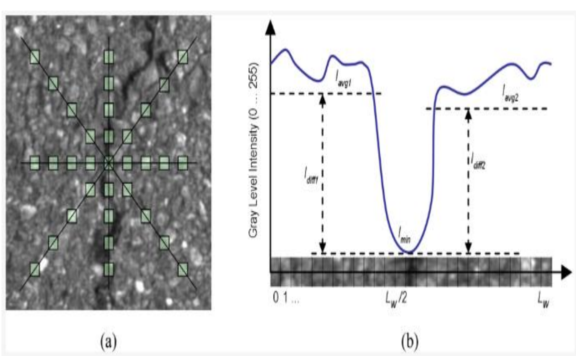

Fig.[6] The four linear windows at 0°, 45°, 90°, and 135°; and (b) the symmetry profile of a cross section of a linear feature, which includes the parameters used in the symmetry check.

V.LIMITATION OF EXISTING SYSTEM

Poor Image quality limits the recognition effectiveness.

Lack of highly configured systems also limits the performance of facial expression recognition.

VI.APPLICATIONS

The system can be used for organizational purposes such as to detect potholes on roads.

Since there are more cars on the road every year, we can use sensors like gyroscopes and accelerators installed on cars to identify potholes and cracks because they provide different readings depending on the type of road

VII.CONCLUSION

The detection and recognition of road sign images in a complex background is one of the key challenges for any researchers. The proposed method describes wavelet energy module and Markov random field for the accurate detection and segmentation of potholes. The detection and segmentation process accuracy are to be improved by combining texture and gray scale information. This paper mainly focuses on detect the pothole regions by using different geometric criterion. The proposed module achieves an accuracy of 95.98% compared to other methodologies which is better than the method proposed by Samarth B, the proposed methodology achieves 93% result in the case of pothole segmentation overlap degree is more than 0.93. The proposed methodology contains some limitations such as, the segmentation process will be time consuming when we use Markov random field. The system detects wrongly as a pothole when we use road cracks and shadow covered potholes as a target image. In the future we will plan to develop a system which speeds up the detection and segmentation processes and improving the detection and classification rate in case of blur and non-uniform lighting conditions

VIII.FUTURE ENHANCEMENTS

Important areas for future work include gathering additional sets of pathole pictures and training the algorithm to achieve greater accuracy than we currently have. The standards used to identify potholes, however, cannot be used in every situation. Therefore, we want to use the modified disparity map to train a deep neural network to recognise potholes.Furthermore, not all road surfaces can be regarded as quadratic. Thus, before using the suggested pothole detection technique, we want to create an algorithm to divide the rebuilt road surfaces into a collection of localised planes.

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