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Method for automated assessment of potholes, cracks and patches from road surface video clips

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Abstract

Potholes, cracks and patches are some types of road surface distresses whose assessment is essential in India. In the current field practices, road distress data assessment is reported to be done through distress data collection and processing of the collected raw data. At present, distress data collection is increasingly being automated by using various imaging systems. However, analysis of the collected raw video clips for distress assessment is still predominantly being done manually. This is expensive, time consuming and slows down the road maintenance management. In this paper, a robust method for automated detection and assessment of potholes, cracks and patches from real life video clips of Indian highways is proposed. In the proposed method, potholes, cracks and patches are detected and quantified automatically using various image processing techniques supported by heuristically derived decision logic. For testing its performance, the proposed method has been implemented under a Windows environment using OpenCV library. The results are evaluated through accuracy and precision-recall metrics and compared with the methods presented by earlier researchers as well as current practices in the field. And the proposed method is found to be more robust and efficient. The information extracted using the proposed method can be used for determining maintenance levels of Indian roads and taking further appropriate actions for repair and rehabilitation.

Keywords: Image Processing; Adaptive Thresholding; Visual Properties Extraction; Automated Distress Assessment

1. Introduction

In a road maintenance management system, the assessment of road surface distresses is one of the important tasks for developing repair and maintenance strategies. Potholes, cracks and patches are some types of road surface distresses whose assessment is essential in India (MORTH, 2004). In the current field practices, road

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distress data assessment is reported to be done through distress data collection and processing of the collected raw data. This uses various road distress data evaluation systems. The evaluation systems currently used in the field can be grouped into three categories depending upon the techniques or methods employed viz. manual, sensor and imaging based systems (TRBE, 2004; Bennett et at., 2007). At present, distress data collection is increasingly being automated by using various imaging systems. However, analysis of the collected raw video clips for distress assessment is still predominantly being done manually. This is expensive, time consuming and slows down the road maintenance management.

The overall review of literature reflects that existing 3D-image based methods have a high cost in terms of equipments and computations; while the vibration (sensor) based methods lack accuracy and reliability (Yu & Yu, 2006; Koch & Brilakis, 2011) with limited applications to road distress assessment. Moreover, existing 2D-video image based methods have been focused individually on cracks (Koutsopoulos et al., 1993; Oh et al., 1997; Tsai et al., 2010) and potholes detection (Koch & Brilakis, 2011) only. In real practice, simultaneous detection and assessment of various distress types is necessary and testing on an even large database of video clips or frames is required for accurate distress assessment and validation of the results. Further, no method are available that can be efficiently applied for automated detection and measurement of potholes, cracks and patches in one pass from real life video clips of Indian highways. Development of such method will enable us to save considerable time and manpower resources while processing the large database of video frames collected for road condition assessment. The key challenges before us are the automated detection and assessment of these distresses from real life video clips collected without any artificial lighting systems. In such video clips, in addition to road distress features, there are images of objects, different road markings and different shadows of various objects (vehicle parts, man, trees, poles) that often occur and these constitute noise (Lokeshwor et al., 2013).

In this paper, a robust method for automated detection and assessment of potholes, cracks and patches from real life video clips of Indian highways is proposed. In the proposed method, potholes, cracks and patches are detected and quantified automatically using various image processing techniques supported by heuristically derived decision logic. The decision logic is derived based on the three main distinctive visual properties of these distresses. The first property is the visual texture as given by standard deviation (*STD*) of the pixels intensities representing the distress region, while the second property is the shape of the distress region as given by circularity (*CIRC*) and the third property is the dimension of the distress region as given by average width (*W*). The proposed method is performed in two stages. In the first stage, the database of video clips captured with/without distress is processed using a fast video segmentation algorithm called "Distress Frames Selection (DFS)" algorithm for automated separation of the video frames having distress from those video frames without any distress. In the second stage of processing, the database of video frames having distress are subjected to an algorithm called "Critical Distress Detection, Measurement and Classification (CDDMC)" algorithm for automated detection and assessment of potholes, cracks and patches in one pass. This algorithm consists of five steps: (1) Image Enhancement, (2) Image Segmentation, (3) Visual Properties Extraction, (4) Detection and Classification by Decision Logic and (5) Quantification. The result is four different types of frames category viz. *frames with potholes*, *frames with cracks*, *frames with patches* and *frames without critical distress*. Besides, frame regions are also tagged with the type of distress identified (viz. potholes, cracks and patches) while the extracted information or measurements are reported in a printable format.

Nomenclature

STD	standard deviation of pixel intensities representing objects region
CIRC	circularity of objects region
W	average width of objects region

2. Proposed Method

The objective of this study is to develop a robust method which has the capability to detect and measure potholes, cracks and patches accurately from real life video frames of Indian highways having bituminous surfaces. With regard to this objective, the present study started with the personal experience of the occurrence of various forms of potholes, cracks and patches on Indian highways. The distinctive visual characteristic of these distresses such brightness, shape, size and location are further investigated to build a heuristically derived decision logic for their accurate identification and classification. Further, real life video clips of Indian highways at different places are captured using two existing camera based imaging systems and they are segmented automatically into two different types of frames category (*frames with distress* and *frames without distress*) using a fast video segmentation algorithm called DFS algorithm. Then, database of *frames with distress* is processed with the proposed algorithm called CDDMC algorithm for automated detection and measurement of potholes, cracks and patches in one pass.

2.1. DFS Algorithm

DFS algorithm applied in the proposed method is the one presented by Lokeshwor et al. (2013) for segmentation of frames with/without distress from road surface video clips. In the presented algorithm, the video frame extracted out of a raw video clip is subjected to various image processing techniques, supported by user defined decision logic for accurate detection of road surface distresses. The main steps in this algorithm are the segmentation of distress pixels from the background pixels of a video frame using an adaptive thresholding technique and the development of a user defined decision logic for categorization of the video frame based on the area covered by the distress pixels (Lokeshwor et al., 2013). The result is two different types of frames category viz. *frames with distress* and *frames without distress.* In this algorithm, a road video frame is considered for *frames without distress* category if total area of objects (distress pixels) is less than 177 sq.cm. The remaining frames which do not belong to *frames without distress* are grouped into *frames with distress* category.

2.2. CDDMC Algorithm

CDDMC algorithm is applied in the proposed method for automated detection and measurement of potholes, cracks and patches in one pass from a sequence of video frames. This algorithm is developed by considering a collective set of three visual properties of potholes, cracks and patches, which have been identified in real life video images of Indian roads. This collective set of identified visual properties includes the following:

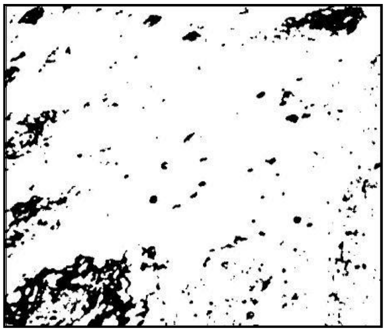
- IMAGE TEXTURE: The image texture inside a pothole, crack and patch is more contrast and varying than the surrounding area i.e. distress free road surface area. However, the degree of contrast variation varies depending upon their types. For instance, contrast variation inside a pothole region is much more than a patch region in the same image.
- SHAPE FACTOR: The shape of a pothole and patch are approximately more circular while the shape of a crack is approximately more elongated. Their shape factor is measured in terms of circularity which varies depending upon their surface area and perimeter.
- DIMENSION: The dimension of a pothole and patch are having higher width than cracks. The dimension of pothole, patch and cracks are expressed in terms of average width.

In this algorithm, all the frames in the *frames with distress* category are grouped into four categories viz. *frames with cracks*, *frames with potholes*, *frames with patches* and *frames without critical distress(NCD)* based on heuristically developed decision logic (Algorithm step no. 12). In this decision logic, a video frame belongs to *frames with cracks* category if the frame contains at least one crack; it belongs to *frames with potholes* category if the frame contains at least one pothole; it belongs to *frames with patches* category if the frame contains at least one patch; it belongs to *frames without critical distress* category if otherwise. This algorithm basically comprises of five components: (a) Image Enhancement (Algorithm step nos. 3 and 4), (b) Image Segmentation (Algorithm step no.5), (c) Visual Properties Extraction of Objects (Algorithm step nos. 6 to 11), (d) Detection & Classification of Distresses by Decision Logic (Algorithm step no. 12) and (e) Quantification (Algorithm step no. 13). The algorithm which is developed for the automated detection, measurement and classification of *frames with potholes*, *frames with patches, frames with cracks* and *frames without critical distress* from a sequence of road video frames is listed below:

1. *Input a sequence of video frames;*
2. *Select the first frame;*
3. *Convert its default 24-bit depth format into 8-bit depth format by selecting its blue channel;*
4. *Apply median filtering for image enhancement (Gonzalez & Woods, 2008);*
5. *Apply weighted mean based adaptive thresholding to convert enhanced image into binary image with black pixels representing objects of interest (Bradski & Kaehler, 2008);*
6. *Apply morphological erosion to add black pixels to bridge the gaps in binary image (Bradski & Kaehler, 2008);*
7. *Apply morphological dilation to remove isolated black pixels or their small cluster (Bradski & Kaehler, 2008);*
8. *Apply morphological erosion again to add black pixels to the binary image;*
9. *Apply connected component labeling (Chang et al., 2004) and chain coding techniques (Yang et al., 1994) to count the number of objects or regions of interest and estimate the area (A) and perimeter (P) of each of the object;*
10. *Filter out all the objects whose $A<177cm^2$ (Non-Critical Objects) in the binary image;*
11. *Determine STD, CIRC and W of each of the remaining objects (Critical Objects i.e. objects whose $A >=177cm^2$);*
12. *Classify each object into four types using heuristically derived decision logic:*
    Type (object) =
    (a) Potholes, if STD >= 10 & CIRC >= 0.10 & W >= 60mm; (1)
    (b) Patches, if 5 <= STD > 10 & CIRC >= 0.40 & W >= 60mm; (2)
    (c) Cracks, if STD >= 5 & CIRC <= 0.30 & W < 60mm; and (3)
    (d) Non-Critical Distress(NCD), if otherwise; (4)
13. *Store the video frame along with the extracted and quantified information in its corresponding category type folder;*
14. *Repeat steps 3 to 13 for all remaining video frames;*
15. *End.*

The procedure applied to extract distress information using the proposed algorithm is shown in Fig.1. In Fig.1, image in column (a) is original image with potholes and patch; column (b) is binary image B after median filtering (i.e. after random noise reduction in column (a) image), and adaptive thresholding (i.e. after object segmentation in column (b) image); column (c) is binary image B_E after erosion (i.e. after joining disparate black pixels in column (b) image); column (d) is binary image B_{ED} after dilation (i.e. after reduction of individual black pixels or their small clusters in column (c) image); column (e) is binary image B_{EDE} after erosion; column (f) is the extracted properties after component labeling & chain coding in B_{EDE} where *CO1* = First biggest critical object (*CO*), *CO2* = Second biggest *CO, CO3* = Third biggest *CO;* column (g) is extracted information reporting the detected distress types and their measurements with POTHOLE_REPORT representing information of detected potholes using Equation (1), PATCH_REPORT representing information of detected patches using Equation (2), CRACKS_REPORT representing information of detected cracks using Equation (3), and Non_CriticalDistress_REPORT representing information of detected *NCD*s using Equation (4).

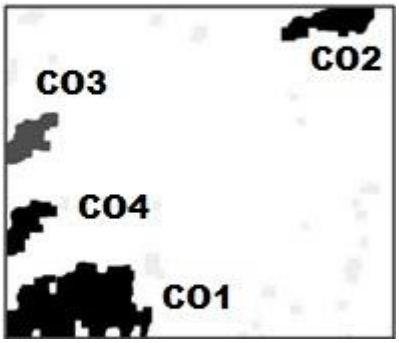
Fig.1. (a) Original image;



(b) B;

(c) B_E;

(d) B_{ED};



(e) B_{EDE};

```
CO1std=19.241267
CO1circ=0.218852
CO1width(m)=0.119532
CO1length(m)=1.467064
CO1elongation =12.273378
CO1.IS.POTHOLE
CO2std=21.582498
CO2circularity=0.340451
CO2width(m)=0.079357
CO2length(m)=0.562378
CO2elongation=7.086639
CO2.IS.POTHOLE
CO3std=7.001114
CO3circularity=0.432691
CO3width(m)=0.082701
CO3length(m)=0.418723
CO3elongation=5.063089
CO3.IS.PATCH
EXTRACTED.VISUAL.PROPERTIES
```

(e) extracted visual properties;

```
POTHOLES_REPORT.................................
totalNumberPotholes=3
totalPerimeterPotholes(m)=5.450000
totalAreaPotholes(sq,m)=0.253873
relativeAreaPotholes(extent)_PC=8.45
PATCH_REPORT....................................
totalNumberPatch=1
totalPerimeterPatch(m)=1.000000
totalAreaPatch(sq,m)=0.034918
relativeAreaPatch(extent)_PC=1.1634
CRACKS_REPORT...................................
totalNumberCracks=0
totalPerimeterCracks(m)=0.000000
totalAreaCracks(sq,m)=0.000000
relativeAreaCracks(extent)_PC=0.000
Non_CriticalDistress_REPORT.................
totalNumberNCD=0
totalAreaNCD(sq,m)=0.000000
relativeAreaNCD(extent)_PC=0.000000
```

(f) report

3. Test Results and Discussions

3.1. Test Platform and Samples

For testing its performance, the proposed algorithm presented in this paper has been implemented in a Windows environment (HP COMPAQ 6710b Laptop with Intel Core ™ 2 Duo CPU@ 2.00 GHz 2.00 GHz, 3 GB RAM and OS Windows Vista) with the help of Visual Studio 2008 (VC++) and OpenCV1.0 Library. A database of 1275 video frames with distress has been selected randomly from the results obtained after applying *DFS* algorithm to various video clips. The video clips have been captured from various parts of national highways in India by using existing camera based imaging systems without any artificial lighting. Out of 1275 images, 283 monochromatic images have been captured by using ARRB NSV on NH-2 near Agra, India. Each image covers 3m length by 2.5 m width of the road with a frame resolution of 1280X960 pixels and pixel size of 2.5 mm x 2.5 mm. The remaining 992 video images have been captured by using a digital camera (Kodak easyshare) in a running passenger van (Tata Magic) on State Highway No.1 (Mayailambi), Manipur, India. Each color image covers approximately 1.5 m length by 2m width of the road surface with a frame resolution of 640x480 pixels and pixel size of 3.125mm X 3.125mm. The test samples contain features such as normal roads, distress like potholes, cracks, patches, discoloration, dark spots and shadows of trees, and vehicles parts.

3.2. Performance Evaluation of CDDMC Algorithm

The test result obtained using the proposed algorithm was evaluated through accuracy and precision-recall metrics and compared with manual method using ImageJ Software (Rasband 2011). In this paper, *accuracy* indicates how many of the *frames with cracks, potholes or patches* and *frames without cracks, potholes or patches* are correctly identified (both True Positives and True Negatives) out of the video clip by the algorithm. And *precision* indicates how many of the *frames with cracks, potholes or patches* identified by the algorithm are actually correct or true positives, while *recall* indicates how many of the true values (both True Positives and True Negatives) identified by the algorithm are actually True Positives or correctly identified *frames with cracks, potholes or patches*. For performance measurements of the developed algorithm, the *accuracy*, *precision*, *recall* and *error* were calculated using Equations (5-8).

$$Accuracy\ [\%] = \{(TP + TN) / (TP + TN + FP + FN)\} * 100 \tag{5}$$
$$Precision\ [\%] = \{(TP) / (TP + FP)\} * 100 \tag{6}$$
$$Recall\ [\%] = \{(TP) / (TP + FN)\} * 100 \tag{7}$$
$$Error\ [\%] = \{(FN + FP) / (TP + TN + FP + FN)\} * 100 \tag{8}$$

Where, TP =True Positives, TN=True Negatives, FP=False Positives, and FN=False Negatives

From the detail analysis of the results, it was found to achieve an overall accuracy of 97% with 95% precision and 81% recall in detecting *frames with potholes,* overall accuracy of 94% with 93% precision and 98% recall in detecting *frames with cracks,* and overall accuracy of 90% with 8.5% precision and 19% recall in detecting *frames with patches*. These three sets of performance measures validate that most of the potholes, cracks and patches can be correctly identified from real life video images of Indian highways. Further, the results were also compared with manual processing method such as NSV Processing Toolkit supplied with ARRB NSV at Central Road Research Institute and found to be 60 times faster in processing one such video frame. Thus, a considerable amount of time (approximately 60 times faster), money and manpower resources could be saved in processing of road video images using the proposed algorithm. Much more savings could have been achieved if we had used higher speed computer with a larger memory (Lokeshwor, 2012).

Examples of processed video frames using the proposed algorithm are shown in Figs.2 to 5. In Fig.2 to 5, images in column (a) are original images with potholes, cracks and/or shadows; column (b) are binary processed images obtained after applying the CDDMC algorithm in column (a) images and column (f) are the extracted visual properties of critical objects in column (b) images, where *CO1* = First biggest critical object (*CO*), *CO2* = Second biggest *CO, CO3* = Third biggest *CO.* In Fig.4.(c) and Fig.5.(c), shadows of trees or vehicle parts seen in their corresponding original images were truly detected as *NCD*s (i.e. not potholes, cracks or patches) by the proposed algorithm since their collective visual properties were not matching with that of potholes, patches and/or cracks as defined in the heuristically derived decision logic. For instance, CO1 in Fig.4.(b) was found to be having STD of 7.64, CIRC of 0.20 and W of 124.2 mm. Thus, the object which represents the vehicle parts shadow was not considered truly to be pothole, crack or patch. Similarly, CO1 in Fig.5.(b) was also found to be having STD of 14.61, CIRC of 0.077 and W of 85.9 mm. Thus, the object which represents the trees shadow was not considered truly to be pothole, crack or patch. A shadow may satisfy the condition of one of the identified visual property (say, *CIRC*) that a pothole, patch or crack possesses in a road video image. However, fulfilling all the conditions of the collective set of visual properties (*STD*, *CIRC*, *W*) pertaining to these three specific distresses is found to be very rare. Thus, the use of the aforementioned collective set of visual properties of a road surface distress is found to be very promising and reliable for its accurate detection and classification.

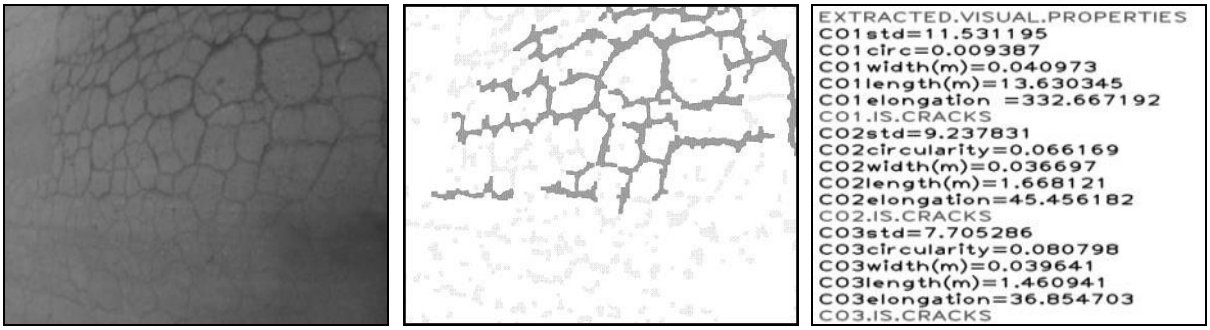


Fig.2. (a) Original image with cracks; (b) processed image; (c) extracted visual properties

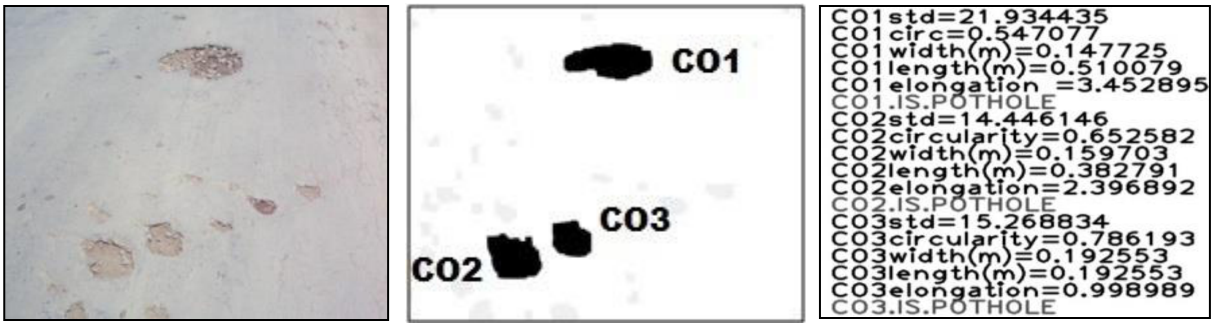


Fig.3. (a) Original image with potholes; (b) processed image; (c) extracted visual properties

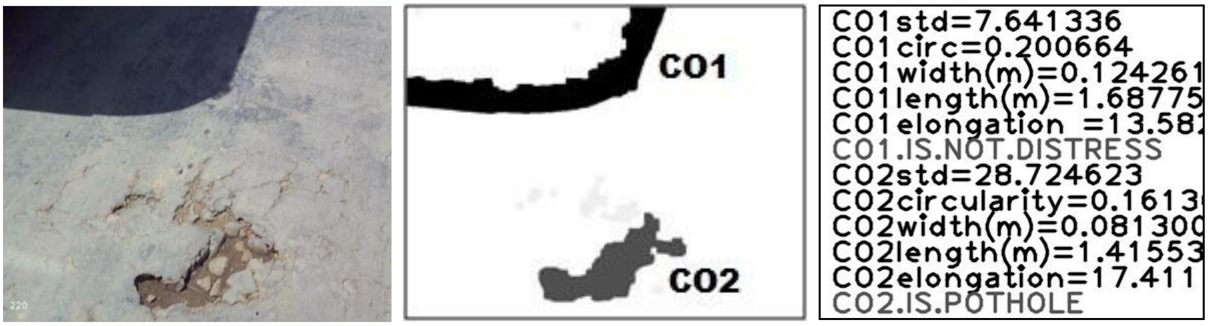


Fig.4.(a) Original image with shadow &pothole; (b) processed image; (c) extracted visual properties

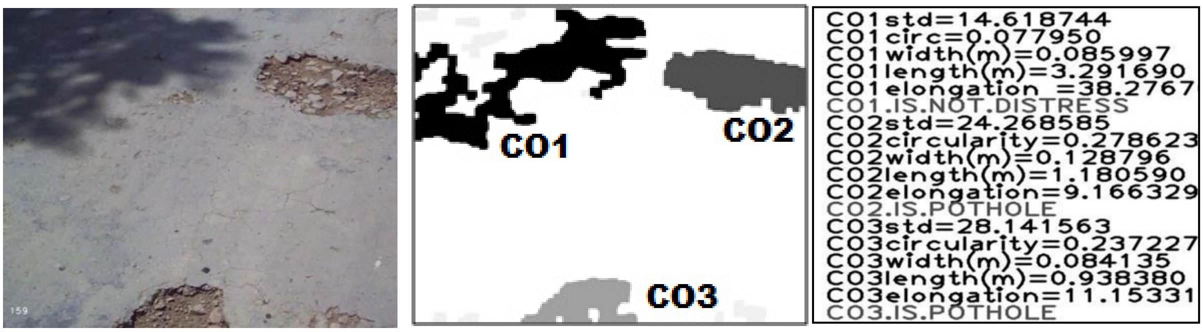


Fig.5.(a) Original image with shadow &potholes; (b) processed image; (c) extracted visual properties

4. Conclusions and Future Directions

In this paper, we have presented an efficient and robust method for automated detection and measurement of potholes, cracks and patches from a sequence of road surface video frames in one pass. The presented *CDDMC* algorithm can detect and measure these three specific distresses efficiently and accurately in one pass using various image processing techniques supported by the heuristically derived decision logic. This algorithm incorporates and establishes the importance of using a collective set of distinctive visual properties of road surface distresses in the context of automated road video data processing for speedy and inexpensive road condition assessment. The collective set of visual properties of these distresses that are identified in video images of Indian highways having bituminous surfaces includes image texture (standard deviation), shape factor (circularity) and dimension (average width) and they are found to unique and different for each distress type. For distresses detection and classification, the collective set of three visual properties (*STD*, *CIRC*, and *W*) that are already extracted out of a critical object in the earlier step were compared with the aforementioned heuristically derived decision logic. If the collective set of extracted visual properties satisfies the conditions pertaining to potholes, then the critical object was classified as potholes and the corresponding video frame was categorized as *frames with potholes*. Similarly, if it satisfies the conditions pertaining to cracks or patches, then the critical object was classified as cracks or patches, as the case maybe, and the corresponding video frame was categorized as *frames with cracks* or *frames with patches* accordingly. If all the three conditions are not satisfied, then the corresponding video frame was categorized as *frames without critical distress*. Further, the area, extent and total number of each identified distresses were computed and reported as per the Indian guidelines. And this information can be used for determining maintenance levels of Indian roads and taking further appropriate actions for repair and maintenance. However, the presented method couldn't deliver high accuracy if few objects such as bleedings, manholes, black colored road markings and discoloration spots appear very similar to the visual characteristics of potholes, cracks and patches.

In future, there is scope for further development of algorithms for the automated classification of cracking types and the measurement of severity levels for potholes and cracks. This may be possible by taking consideration of a collective set of the visual properties of these distresses along with their roughness data or profiles.

NOTE

The research sponsoring organization and the authors do not endorse any proprietary products or technologies mentioned in this paper. These appear herein only because they are considered essential to the objective of this paper.

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