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A Machine Learning Approach for Detection and Suppression of Shadow or Wet Road Surfaces

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ABSTRACT- In advanced driver assistance system detection of road surfaces is an important task. Few algorithms have been proposed in past to detect the road surfaces based on intensities. However, problem arises in detection process is due to the presence of shadows or wet road surfaces. Here we have proposed a novel algorithm for detection of shadows with the help of machine learning approaches. Initially shadow is being detected with the help of a threshold-based approach followed by windowing-based method. The detected shadow region gets confirmed with the help of a set of features and classifier. The detected shadow or wet pixels are in painted to obtain set of pixels without shadow for road classification problems. The simplicity and accuracy of the algorithm makes it robust and can be used as a part of road surface detection algorithm.

Keywords: Intelligent vehicle, ADAS, Forward difference, Seed point, Windowing.

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1. INTRODUCTION

Most road accidents are the result of human mistake, which is preventable with advanced driver assistance systems (ADAS). There are many safeties critical ADAS applications out of which road surface classification is one important aspect. Due to the complexity of road surface textures few algorithms have been proposed in past. Shadow creates a confusion to detect road surfaces due to variation in intensity. Apart from that shadow detection and removal is an important image processing problem in many vision-based algorithms. Along with shadow wet road also creates similar type of problem in image classification because of its appearance. The algorithm proposed here to detect shadow is also applicable to wet road surface detection. In past many researchers have proposed many algorithms for detection of shadows. Some of them are discussed in below paragraph.

Images offer a detailed sense of the surroundings, and they have several advantages, especially when utilised in vision-based systems. To help automobile systems, one such use of vision-based analysis is the categorization of various types of road surfaces, such as cement, asphalt, sand, rough, and grass. The categorization of road surfaces in relation to still photographs of the asphalt or concrete macro texture [1],[2],[3] has already been the subject of research since long. Its computational complexity, however, makes the response time a little late. Raj et. al. [4] put forth a unique concept for an image-based system for detecting road surfaces. This system is based on basic image processing methods as Canny edge detection, Hough transform, contours, intensity histograms, and image segmentation. By applying such basic techniques to continuously streaming video, the imaging system's processing time and computing complexity are decreased. In their algorithm, to distinguish between asphalt road and cement road, only intensity histogram is considered. But the real challenge comes when a portion of road surface is covered under static shadow and /or due to wet condition. To distinguish between asphalt and cement road Raj et. al. applied the histogram analysis method and expecting the problem of shadow or wet road condition. So shadow detection or wet road detection becomes a common problem while dealing with road surface classification problem for ADAS (advanced driver assistance system). Also, certain computer vision applications, including edge detection, image segmentation, object recognition, video surveillance, and stereo registration [5],[6],[7] have been negatively impacted by shadows in pictures. When a light source's direct light is partially or completely blocked, shadows result. As explained by Jyothisree et. al. [8], there are two categories of shadows: self-shadow and projected. The area of an item that is not directly lit up by light is known as the self-shadow (also known as the attached shadow). The dark area that an item projects onto a surface is known as its cast shadow. Umbra and penumbra regions are subsets of the cast shadow. The umbra portion of a cast shadow is where all direct light is blocked, whereas the penumbra region is when direct light is only partially obscured. In [8],[9],[10], they have suggested an approach for detecting shadows is based on the Tricolor Attenuation Model. There are three key steps in it: Getting the TAM image, Increasing the

TAM image's contrast and combining an intensity image with an improved TAM image. The more popular segmentation approaches combine shadows and objects into a single blob because shadow locations are close to object points. These factors result in two significant drawbacks: The first is that shadows distort the object's shape and cause an inaccuracy in every measurement of its geometrical features (that varies during the day and when the luminance changes). This has an impact on both categorizing and evaluating the location of moving objects like traffic control systems that must examine the trajectories of automobiles and pedestrians on a road. The second issue is that the shadows of many objects may appear to be adjacent to one another when they are not, leading to the perception that they have merged in one which affects many surveillance algorithms. In [11] [12] proposed a method to avoid all these issues using HSV colour space. In their work, first they have subtracted the background using Gaussian Mixture Model which is capable enough to classify a pixel as background or fore ground with the help of thresholding. Then using some post processing techniques shadow can be suppressed with the help of RGB and HSV colour space. Tian et. al. [13] proposed a method of shadow detection concentrating on a single outdoor image's shadows. The tricolour attenuation model (TAM) that has been developed to explain the attenuation relationship using the theory of image formation, a relationship between a shadow and its non-shadow background is determined. The spectral power distribution (SPD) of daylight and skylight, which is approximated using Planck's blackbody irradiance equation, is used to establish the TAM's parameters. A multistep shadow detection technique is presented with the help of basic image processing techniques to extract shadows based on the TAM. According to [14] the brightness component in HSI space is transformed by NDUI shadow exponent transformation based on the enhancement of the blue component. The transformed image is then segmented by threshold value, and the road main body is extracted after the small area spot is removed and the adaptive structural element morphology closing operation. In [15],[16]. it has been proved that there has been much research on slope monitoring and picture digitization technologies. The findings demonstrate that the digital image measuring method to the conventional slope monitoring method clearly offers advantages. The shadow can be removed using the edge information [17], only by considering the interior edges. High quality road surfaces deteriorate for a variety of reasons due to natural processes or human actions, and this scenario cannot be avoided. As deterioration grows more severe, it creates several dangers for those using the roads, and maintenance becomes expensive and time-consuming. Preventive measures can be taken later or before they are required, therefore the "run to failure" theory is not the best approach. The approaches based on real-time monitoring [18,19], assessing the existing situation and projecting future growth to choose the proper maintenance in every time slot are more precise and effective. A deep learning-based approach is proposed for crack diagnosis [20] is proposed but that do not deal with road surface detection or shadow detection.

In this paper we have proposed a novel method do detect shadows from an image using the methods of artificial intelligence and machine learning. Initially shadow portions are detected using histogram subtraction and connected pixel analysis, which then reconfirmed using machine learning approach. This method is also applicable to wet road detection which can be helpful for driver in advanced driver assistance system. *Section 2* represents the proposed algorithm followed by result analysis in *section 3* and conclusion in *Section 4*.

2. PROPOSED METHOD

To detect shadow in each image we first tried to find out the shadow pixels using histogram analysis followed by seed point and region growing method. The detected shadow points are reconfirmed as shadow region using artificial intelligence method.

2.1 Intensity Analysis

At first all the pixels are being examined whether it is a shadow or non-shadow pixel. All the global and local statistics of the image has been used. The intensity histogram of the image has been observed initially. Then the forward difference has been observed from the adjacent histogram counts in the histogram array. This array is termed as *sub* and is calculated as per *equation (1).*

$$sub(j) = int(j+1) - int(j), j \in [0,254] \quad (1)$$

where *int (j)* is the count of the histogram at j^{th} index which is the value in gray scale. *sub(j)* is denoted for the forward difference at j^{th} index. As there is a high chance that the image might be affected by radiation from surface or by any other camera parameters, so to get a better smooth image *equation (1)* can be recomputed as explained in *equation (2).* The index of the maximum value obtained from the array in *equation (2)* is the threshold value which can separate the shadow from the background.

$$sub1(j) = sub(j+1) - sub(j), j \in [0,254] \quad (2)$$

The underlying assumption of this method of threshold calculation is that the shadow covers a portion in the image and the remaining portion of the road surface mage is not covered with any object. It is important to note that the algorithm that is suitable for shadow detection is also suitable for wet road detection. Fig1 represents the original image, its histogram, forward subtraction array for a wet road.

2.2 Shadow Candidate Pixel Identification

Once the threshold value is calculated, which is the index of the maximum value of the $sub1$ array obtained from *equation (2)*, now our job is to identify the shadow candidate pixels individually. To methods have been applied to detect the shadow candidate pixels. At first with the help of obtained threshold value all the pixels are being tested using *equation (3).*

$$z(x,y) = I(x,y) < Th \quad \forall x,y \quad (3)$$

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Where *z(x,y)* is the detected shadow candidate pixels, *I(x,y)* is the original intensity image and *Th* is the obtained threshold value. But it has been observed that this method is not suitable to detect the shadow candidate pixels for all possible shadow or wet road images. The reason behind this is that the threshold value obtained is not the best threshold value for all categories of images. This may be due to varying atmospheric conditions or camera parameters etc. So, we have tried another approach for initial scanning. The second approach is a combination of two stages: windowing and connected pixel detection. To do this, for each pixel in the original image an *N x N* window is imposed first. The value of *N* is decided empirically. In our case the value of N which gives suitable result is 11. Each pixel is tested to be a shadow or non-shadow pixel using *equation (4).*

$$Z_{i,j} = \left(S_{i,j} - max\left(W_{i,j}^{N\times N}\right)\right) < Th \quad \forall\, i,j \qquad (4)$$

The pixels which satisfy the above equation are classified as shadow pixels, other pixels are classified as non-shadow pixels. In *equation (4)*, $Z_{i,j}$ represents the final set of location of all shadow pixels. $S_{i,j}$ represents the current intensity image of location *(i,j)*. $W_{i,j}^{N\times N}$ is the set of *N x N* neighborhood pixels of location *(i,j)* and *Th* is the threshold value obtained in *equation (2)*. The shadow pixels obtained in this method contains several false detections, which is the number of background pixels that are classified as shadow pixels. The false detection can be minimized with the help of connected pixel calculation method which is explained in *equation (5)*.

$$\sum_{i-k}^{i+k}\sum_{j-k}^{j+k} Z_{i,j} > L, \qquad L < k \times k \qquad (5)$$

The pixels that are being classified as shadow pixels $Z_{i,j}$ are re-examined in its neighborhood $k \times k$. In the said neighbourhood if L number of connected shadow pixels are found, then the corresponding pixel is termed as shadow pixel. It has been observed that the neighboring pixels gives an idea of connected pixel components, so that any isolated pixel which is falsely classified as shadow pixel in earlier stages are discarded in this stage. Also, we have observed that a neighbor of 5 x 5 is sufficient to classify a pixel as shadow or non-shadow pixel. The combination of *equation (4)* and *(5)* gives better shadow pixel detection result in comparison to equation (3) alone. *Fig. 2* gives a comparative study of these two initial scanning processes. In *fig. 2* the threshold-based scanning indicates the first method that is the method adopted in *equation (3)* and the two-stage scanning method. *Fig. 3* represents the original image, shadow detected in first stage of two stage scanning method and the shadow detected in second stage of the two-stage scanning method. Here we can observe from figure that the shadow obtained using the first stage of two stage scanning method is better than that of the threshold-based approach in wet road image. So, for the upcoming further identification process we have chosen the two-stage scanning method.

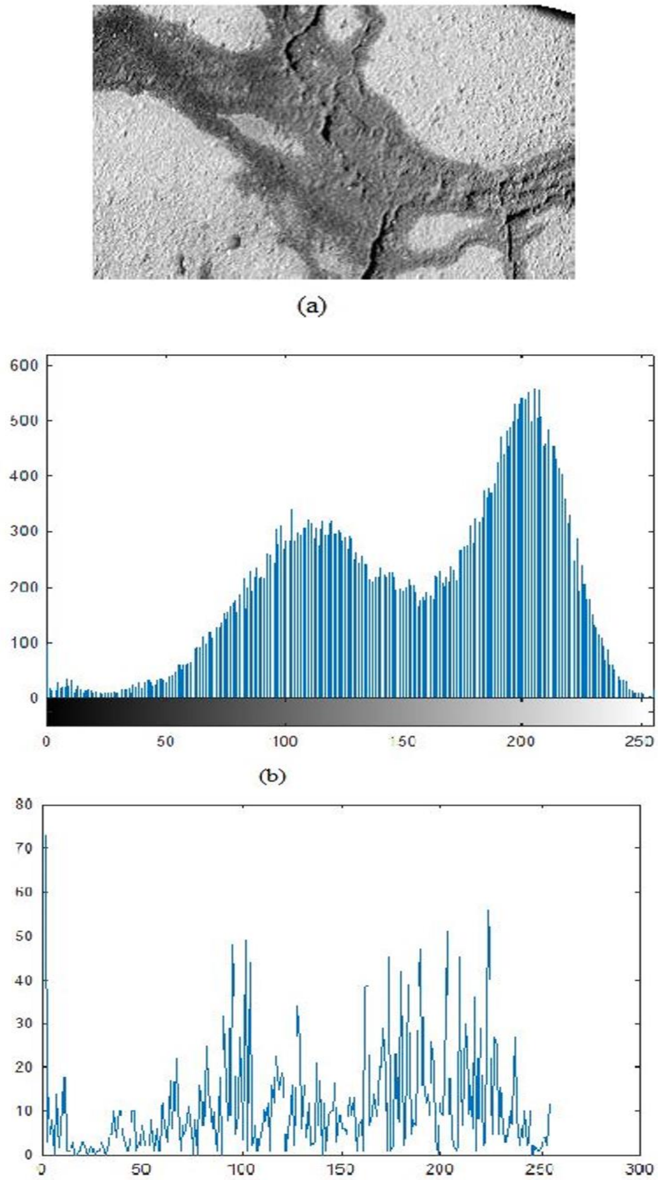
2.3 Shadow Candidate Pixel Confirmation

The shadow pixels detected in the above stage contains shadow in a region. In general, individual pixels identified as shadow about which is trivial. To refine our result, that is to identify shadow regions perfectly we then re-examine the shadow regions with the help of machine learning and artificial intelligence. First the image is being divided into small regions which contain shadow and non-shadow regions with $p \times p$ dimension as shown in fig4. Three features are tested to classify shadow region from non-shadow region. They are range, mean and standard deviation. These four features are defined in *equation (6).*

$$Range = \max\big(Z(i,j)\big) - \min\,(\mathrm{Z(I,j)}) \;\; \forall\, i,j$$

$$Mean = \frac{\sum Z(i,j)}{N} \qquad \forall\, i,j \qquad (6)$$

$$Standard\ deviation = \sqrt{\frac{\sum (Z_{i,j} - Mean)^2}{N}}\ \forall\, i,j$$



(a)

(b)

(c)

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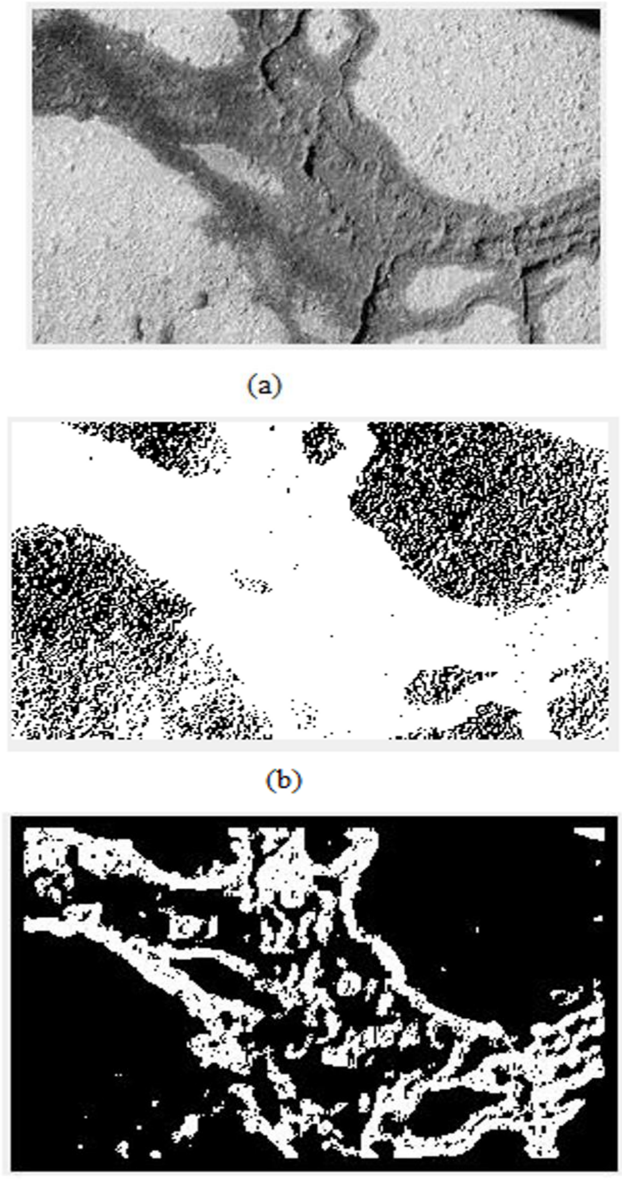
Fig. 1: (a) Original image (b) Histogram of the image (c) Forward Difference



(a)

(b)

(c)

Fig 2: (a) original image (b) threshold-based approach (c) two stage scanning approach

Where Z is the set of pixels, or we can call it as a portioned image which is either shadow or non-shadow. N is the total number of pixels in Z. Fig 5 represents how these three features are sufficient to distinguish between shadow and non-shadow regions. In order to categorize, we employed a naive Bayes classifier, which uses the MAP decision rule, which is the most likely decision rule. The Bayes Theorem [21-23] provides a way to determine the likelihood of a given hypothesis by using its prior probability. The matching classifier function is defined as follows to categorize shadow and non-shadow region in *equation (7)*.

$$classify\,(n_1, n_2, n_3, \dots n_n) = argmax\, P(X = x) \prod_{i=1}^{N} P(L_i = n_i | X = x) \qquad (7)$$

Where X represents the conditional class variable with few classes and Li represents the feature variable.

2.4 In painting

Damaged, degraded, or missing portions of an image are filled in during the conservation process of in painting to show a full image. The shadow pixel regions detected in the previous stage with a process called in painting where the detected pixels can be in painted with the help of *equation (8).*

$$I_n = f_n(i,j) = \frac{1}{k*k} \sum_{i-\frac{k}{2}}^{i+\frac{k}{2}} \sum_{j-\frac{k}{2}}^{j+\frac{k}{2}} f_{n-1}(i,j) \qquad n = 1,2,3 \dots N \;\; , \forall i,j \qquad (8)$$

Where n stands for the number of iterations, f_0 stands for the original frame. N indicates the total number of shadows detected pixels. *(i,j)* indicates the detected shadow locations. For a pair of *(i,j)* one value of n is considered.

3. RESULT ANALYSIS

We have evaluated our algorithm by some images downloaded from internet. Also, it is an assumption that the data collection is made up of picture frames that were pulled out of videos that were recorded using a mobile phone camera. Also, it has been suggested that the camera is positioned on the moving vehicle's bonnet when the recordings are being taken. Our suggested approach was implemented using MATLAB 2016 and the Windows 10 operating system. The method was executed on a PC running a 64-bit operating system and an Intel Core (TM) i3-3110M Processor clocked at 2.4 GHz. Although our system uses videos, each frame is considered when predicting the shadow on the road surfaces. An image is taken from internet as shown in figure 1. After converting it into gray scale, it has a dimension of 183 x 275. When the forward difference is obtained, theoretically it is expected to have two peaks because of two different set of pixel values. But this does not happen due to many other parameters present in the gray scale image like camera parameters, atmospheric noise etc. To get better result, we have gone for finding out the forward difference second time which is shown in figure 1. The maximum value in the forward difference gives the threshold value which is used in the next stage to determine the shadow candidate pixels. Prior to going for two stage initial filtration method, we have tried the threshold-based method for selection of shadow candidate pixels as explained in equation (3). Figure 2 shows the result of this method for an obtained threshold value of 50. Due to poor detection, the two-phase detection method is adopted then. Then on each pixel of the intensity image an N x N window is applied. We have chosen the value of N as 11, because 11 x 11 window

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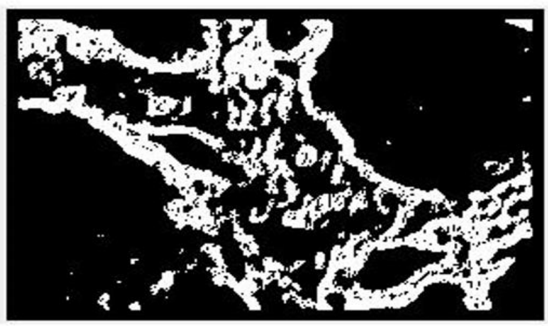
gives better detection. If we increase the value of N, there appears no change in detection and if the value of N decreases results deteriorates significantly. If the difference between the said pixel and the maximum pixel in the window is less than the threshold value, then the said pixel is classified as shadow pixel. The shadow pixels detected in this method contains several false detections. To reduce false detection a strategy has been taken that the shadow pixels appear in a group not individually. So, the pixels detected as shadow must be connected. To find the connected [24] or shadow pixels, first we considered the detected shadow pixels in the previous stage. Then a *K x K* neighborhood is considered around a pixel. We observed that value 5 for *K* gives good result. If we choose value of *K* more than 5 there is no change in result appears. Then in that *K x K* neighborhood if more than 2/3rd of connected pixels are not there, then the pixel is considered as a non-shadow pixel and is discarded from the set of shadow pixels.

(a)

(b)



(c)

Fig. 3: (a) original image (b) detection after first stage (c) detection after second stage

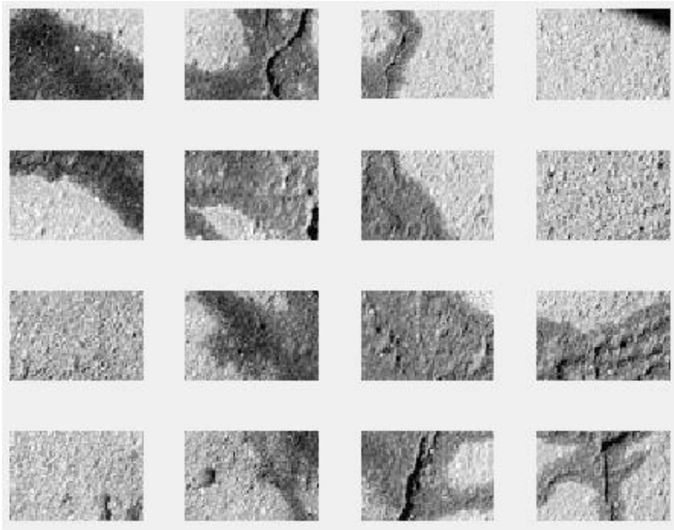


Fig. 4: Partitioned Image with shadow and non-shadow blocks

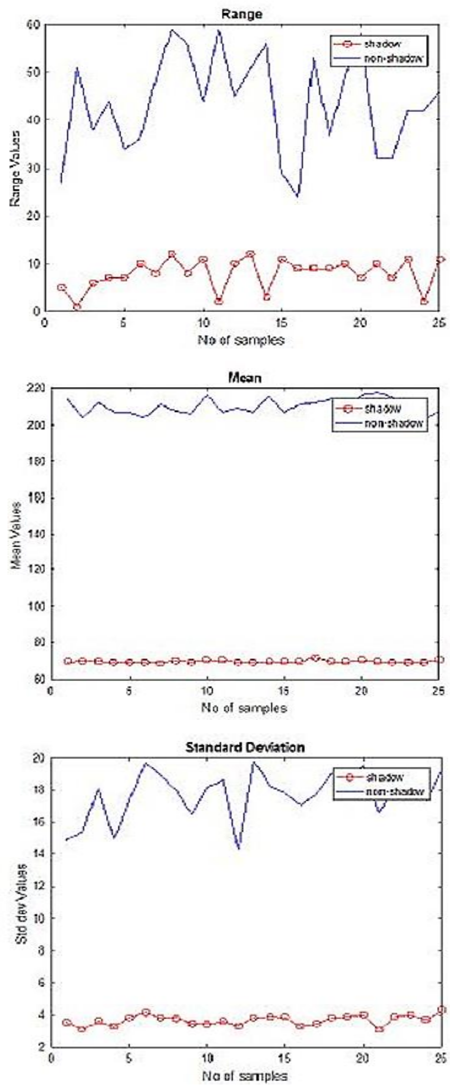


Fig. 5: Range, Mean and standard deviation feature values for different blocks in data set.

To reduce false detection a strategy has been taken that the shadow pixels appear in a group not individually. So, the pixels detected as shadow must be connected. To find the connected or shadow pixels, first we considered the detected shadow pixels in the previous stage. Then a *K x K* neighborhood is considered around a pixel. We observed that value 5 for *K* gives good result. If we choose value of *K* more than 5 there is no change in result appears. Then in that *K x K* neighborhood if more than 2/3rd of connected pixels is not there, then the pixel is considered as a non-shadow pixel and is discarded from the set of shadow pixels.

After detection of shadow region, a reconfirmation of shadow region is being tested with the help of machine learning algorithm. In this method a set of pixels classified as shadow pixels are being retested for shadow or non-shadow with the help of naïve Bayes classifier and set of features described in previous section. Initially a classifier is being trained with the help of small image portions of size *p x p*. Then a portion of the original image of same size is being taken for testing purpose. If the region detected as shadow in this process matches with the shadow region obtained in the previous stage, then the region is confirmed as shadow region. Experimentally we have chosen the value of *p* as 9. The reason is if we choose the value more than 9, then lots of pixels can be removed for a single wrong detection. If we choose the value *p* less than 9 then a smaller number of pixels will be available for training. So, accuracy of the classifier will be poor. *Fig. 6* represents an original frame and the final shadow/ wet portion detected region.

Fig. 6 represents the pictorial output of our proposed algorithm. To compare the quantitative performance of our algorithm, ground truth is required. We have created the ground truth of a frame with the help of Snipping Tool software. *Fig. 7* shows one original frame, corresponding ground truth obtained by Snipping Tool and our output. The accuracy can be calculated using *equation (9)*, where we have considered the number of correctly classified pixels and the total number of shadow pixels in the ground truth. Also, to prove the efficiency of the proposed algorithm we have chosen two more parameters along with accuracy: shadow detection precision (SDP) and shadow detection recall (SDR) [25]. Mathematically they are defined in *equation (10) and (11).*

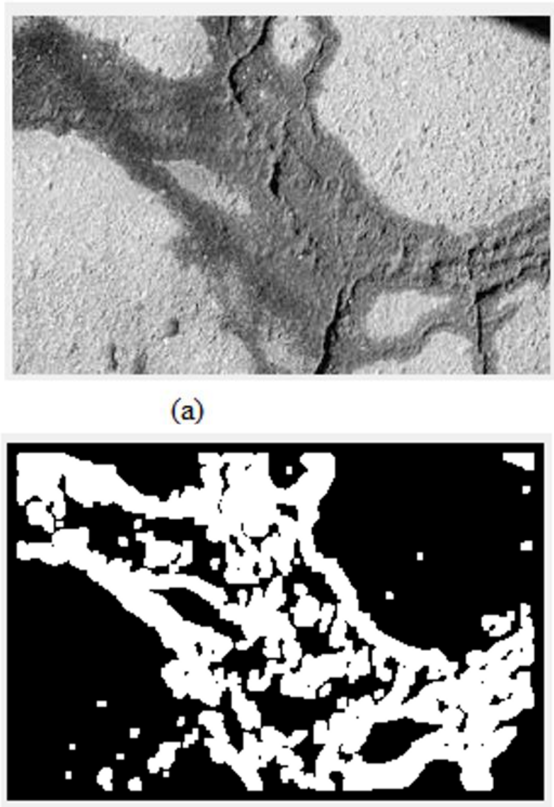
$$Accuracy = \frac{No\ of\ correctly\ classified\ pixels\ as\ shadow}{Total\ no\ of\ shadow\ pixels\ in\ ground\ truth} X\ 100 \quad (9)$$

$$SDP = \frac{TP_{Detected\ Shadow}}{TP_{Detected\ Shadow} + FP_{Detected\ Shadow}} \quad (10)$$

$$SDR = \frac{TP_{Detected\ Shadow}}{TP_{Detected\ Shadow} + FN_{Detected\ Shadow}} \quad (11)$$

where TP stands for true positive, FN stands for false negative, and FP stands for false positive.

After detection of shadow or wet pixels, we will try to do in painting of these pixels with the help of *equation (8)* as explained in the previous section. To do this at first the detected mask is scanned horizontally to know the affected pixel location. After locating the first location, we consider its neighbors in a window of size *k x k*. The value of *k* that we have chosen is 3. The average of all these neighboring pixels replaces the original pixel value and the frame is updated. In the next iteration for the next location, the same process is adopted but here the updated frame in the previous stage is considered while calculation the *k x k* average not the initial image. *Figure 8* shows the original frame and the in painted frame.



(a)

(b)

Fig. 6: (a) Original Image (b) detected wet portion of the image.

(a)

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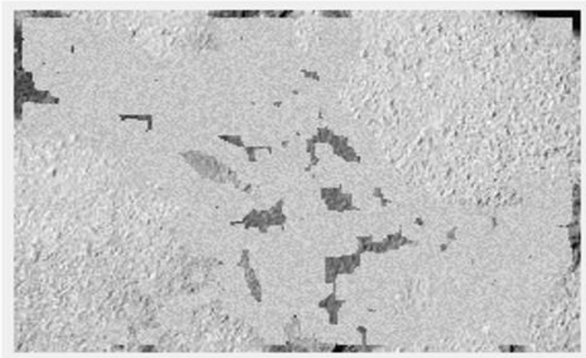
(b)

(c)

(d)

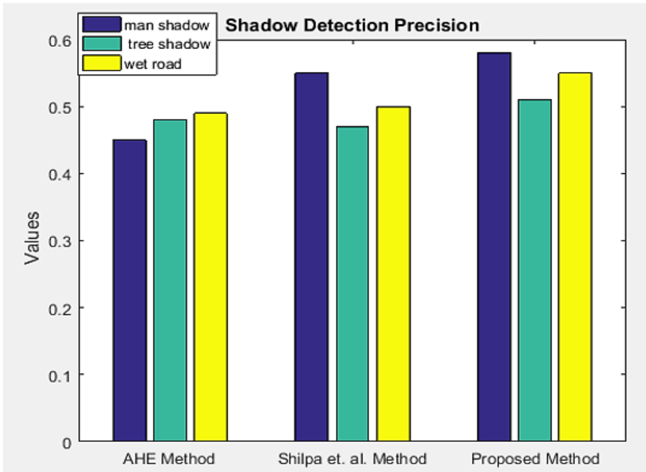
Fig. 7: (a) Original frame (b) affected region cropped manually (c) binary mask as ground truth (d) detected binary mask.

(a)

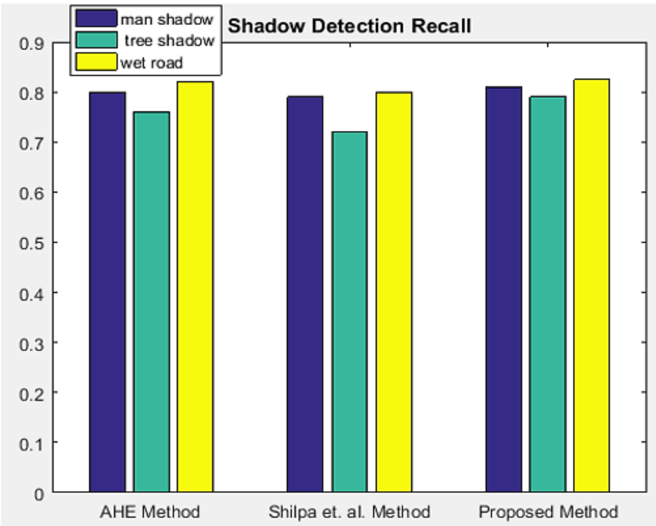


(b)

Fig. 8: (a) original image (b) output after in painting



(a)



(b)

Fig. 9: (a) Shadow detection precision (b) Shadow detection recall

The quantitative performance of our algorithm has been compared with AHE based shadow detection technique [3]. Table (1) shows a comparative study between AHE, Shilpa et. al. [15] and proposed algorithm which clearly indicates the optimality of our algorithm. Also, another two performance estimating parameters SDP and SDR has been analyzed in *figure 9*.

Table 1: Comparative Analysis of proposed method with AHE method in terms of detection accuracy

Image	AHE Method (%)	Shilpa et. al. method	Proposed Method (%)
Wet Road Image	85	86	86
Human Shadow 1	95	93	98
Tree shadow	91	94	97

4. CONCLUSION

Our newly developed machine learning-based technique for detecting shadows makes use of a probabilistic classifier and certain pre-processing procedures. With the aid of a few factors that are taken into consideration by analyzing the intensity variation, it classifies shadow and non-shadow regions. This approach is resilient since it only operates in intensity plane and ignores the effect of color components. With a set of data that we generated, we assessed our system and contrasted it with two already in use. As the algorithm is simple it can be treated as an intermediate tool for road surface prediction while shadows create an issue. The quantitative analysis shows the accuracy of our algorithm. It is quite clear from our result that the shadow or wet road detection capacity of our algorithm is quite high. But the in-painting method that we have applied, though clears the shadow but it cannot completely remove its effects. But it is highly essential for ADAS as stated in introduction that we need these shadows to be removed to predict road surfaces by considering its intensity values. So, using this method shadow pixel will not create any problem for road surface detection especially when differentiation between cement and asphalt road surface is required. For other image processing related works like shadow removal, other or improved in painting methods can be used which can be the future scope of the work.

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