Asian Journal of Electrical Sciences
ISSN: 2249 - 6297 Vol. 2 No. 2, 2013, pp.14-21

Vehicle Braking Performance Improvement By SVM Based Road Surface Detection

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(Received on 14 May 2013 and accepted on 28 June 2013)

***Abstract* – Advance information about the road surface a vehicle is going to encounter can improve the performance of Antilock Braking System (ABS). For e.g. the initial slip cycles caused by the ABS could be avoided, if it is already known that the vehicle is on a surface having a low coefficient of friction (μ). In this paper, an algorithm is developed that detects different road surfaces using streaming video acquired from a camera mounted on the hood of the vehicle. The road surfaces detected here are asphalt road, cement road, sandy road, rough asphalt road (asphalt road which is deteriorating), grassy road and rough road. The value of coefficient of friction (μ) is also given out with the detected surfaces to obtain additional information about the road surfaces. Split μ (a road having different μ conditions on the left and right side of the vehicle) and μ jump (different μ conditions on the front and rear of the vehicle) are also pre detected. One method was not sufficient to achieve the goals of this algorithm. Here several simple techniques like the Canny edge algorithm, intensity histogram, contours, Hough transform and image segmentation were employed and compared with the Support Vector Machine (SVM). To prevent misdetections, the road surface detection during high motion blur is prohibited.**

***Keywords:* Computer vision; Vehicle dynamics; Vehicle safety system; Signal processing; Automotive systems; Electronics in industry and transport**

I. Introduction

Images provide a dense environment perception and their benefits especially when used in vision- based systems are enormous. One such application of vision based analysis is in the classification of different kind of road surfaces like cement, asphalt, sand, rough and grass to provide assistance to automotive systems. Research work already done relates to classification of road surfaces in context with still images of asphalt or concrete macro texture as in [1] or based on spectrum analysis as in [3]. In [2], fast Fourier transform is used to determine the road surface conditions. However, it has computational complexity and the response may be sluggish. Here we propose a novel idea of image-based road surface detection system based on simple image processing techniques like Canny edge detection, Hough transform, contours, intensity histogram and image segmentation and compare with the SVM. Simple image processing algorithms are used on the continuously streaming video thereby reducing time and computational complexity of the imaging system. It avoids the training schemes givenin [4] as decisions are given out instantly. The algorithm is robust as it works even in shadowy conditions. In [5], the decision is taken only with histogram, whereas in the proposed algorithm this technique is used effectively and judiciously to take decisions when edge detection technique is not sufficient.

This algorithm makes the early detection of road surfaces which will allow the vehicle dynamic system to react decisively with the changing road conditions. It also identifies lane marking on cement and asphalt based on Hough transform as in [9]. Split μ and μ jump conditions are also being pre detected and increases the efficiency of ABS. So the stopping distance also reduces.

II. Image Processing Technique

Image processing techniques are employed to develop this algorithm. It is discussed in detail in this section.

A. Canny Edge Detector

Edge detection is used for (i) identification of blurred frames (ii) broad classification among smooth and rough surface (iii) classification of cement and asphalt. The Canny edge detection is performed on the frames with the sensitive threshold values (upper threshold 10000 and lower threshold 4900) and again it is performed with the insensitive threshold values (upper threshold 50000 and lower threshold 9800). If a pixel has a gradient greater than the upper threshold, then it is an edge pixel. If a pixel has a gradient lower than the lower threshold, it is not an edge pixel. If the pixel's gradient is between the upper and the lower thresholds, then it is considered as an edge, only if it is connected to a pixel that is above the high threshold value as given in [7] [8]. The number of edges is then computed.

B. Contours

Contours are connected edges and are used to (i) identify the lane marking (ii) classify rough asphalt from rough road. Contours are drawn on the frame with the threshold value of 210 and again contours are drawn for the threshold value of 75. The reason for choosing the threshold values are mentioned in the section III. The threshold values are chosen such that the pixels brighter than the threshold value are alone identified as in [7] [8]. The number of contours for the threshold value of 75 is alone computed.

C. Hough Transform

Hough transform is used to (i) identify man made partitions on the surfaces (ii) find the line segments (lane marking) in an image given in [9]. The Standard Hough transform is used to map each pixel in image space to a line in Hough space and vice versa as mentioned in [7].

D. Intensity Histogram

Histogram is used to (i) classify sand from cement/ asphalt (ii) classify grass from rough surface. The total number of pixels having intensity values ranging from 150 to 195, 135 to 170 and 50 to 200 are found to classify sand, cement/asphalt and grass respectively taken from [7] [8].

E. Support Vector Machine (SVM)

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non- probabilistic binary linear classifier.

III. Proposed Algorithm and Decision Making

The six main parts involved with algorithm and decision making are (i) blur detection, (ii) broad classification of road surfaces (iii) classification of smooth roads (iv) Classification of rough roads (v) classification of split μ and μ jump (vi) co-efficient of friction for different road surfaces. The procedure below is followed to classify different kinds of road surfaces. The flowchart of the proposed algorithm is shown in Fig.14.

A. Blur Detection

The frames from the streaming video are converted into gray scale. Canny edge detection with sensitive threshold value identifies the motion blurred images since the blurred frames have edges less than 1000. Once blur is detected, those frames are not considered for decision making.

B. Broad Classification of Road Surfaces

To classify rough and smooth surface, Canny edge detection with insensitive threshold value is performed. The insensitive threshold value is chosen such that the problem of shadow and other disturbances are eliminated since shadows form weak edges. Man made partitions like lane marks and patterns on a smooth surface contribute to more number of edges causing misdetection. So lines are detected using Hough transform in the frames to eliminate man made partitions. The edges are then computed on the frames where man made partitions are eliminated. Fig. 7 shows the calculated edges with insensitive threshold for different types of road surfaces. Smooth surface is classified from rough surface since it has less number of edges (less than 1000) when compared to rough surface. Cement, asphalt and sand are classified as smooth. Rough asphalt, rough road and grass are classified as rough.

C. Classification of Smooth Roads

1. Cement and Asphalt Roads with lane marking

A lane marking is a straight line in an image and the gray scale value lies in the vicinity of 210, thereby using contours with the threshold value of 210 and Hough transform, lane marking is identified as shown in the Fig. 1. The threshold value of 210 is chosen to identify lane marking such that the pixels brighter than the threshold value 210 are retained as non zero (white pixels corresponding to the lane marking are alone identified). Canny edge detection with sensitive threshold is performed and the number of edges is computed. Fig. 8 shows the calculated edges with sensitive threshold for different types of road surfaces. Cement has less number of edges (less than 6000) when compared to asphalt as shown in Fig. 8. Once lane marking is detected, it is sure that the surface is either cement/asphalt.

Intensity histogram is used to find the gray scale intensity value of the frame having lane marking. To distinguish asphalt/cement from sand, adaptive threshold is used. The intensity value which is already chosen to classify cement/asphalt is changed to the intensity value of the lane mark detected frame. This technique can accommodate changing lighting conditions in the image and also can be adapted to lane marks. Successive frames are then checked for the intensity levels. If the intensity values are approximately same, the frame is not checked for the other parameters like edges and contours, instead they are simply classified as cement or asphalt.

2. Cement and Asphalt Roads without lane marking

Asphalt/cement has more number of pixels in the range of 135 to 170 as shown in Fig. 10 since these intensity values represent the gray color band of cement/asphalt. If the total number of pixels between the intensity values 135 and 170 is greater than the intensity values ranging from 150 to 195 as in Fig. 12, then it is either cement or asphalt. Canny edge detection having sensitive threshold is again used to classify cement from asphalt similar to the procedure done after the lane marking +has been detected.

3. Sand

Intensity histogram is used to find the total number of pixels in the range of intensity values 150 to 195 and 135 to 170. If the total number of pixels between 150 to 195 ranges as shown in Fig. 12 is greater than 135 to 170, the smooth surface is classified as sand since those intensity values are typical indicators of sand surface.

D. Classification of Smooth Roads

1. Grass

Grass is expected to have more number of pixels lying between the intensity values 50 to 200 because the intensity values for grass is widely distributed as in Fig. 11. So grass is classified from rough road and rough asphalt because the intensity distribution of rough asphalt/rough is not as wide as that of grass.

2. Rough Asphalt

Contours with the threshold value of 75 is used to separate rough asphalt from rough road since the contours for rough asphalt are lesser than 2000 as in Fig. 9. At the threshold value of 75, rough asphalt has less number of connected edgesbecause it does not have pixels brighter than the threshold value 75.

3. Rough Road

For rough roads, the contours with the threshold value of 75 are greater than 2000 as shown in Fig. 9 because the brightness of the pixels on a rough road is mostly greater than the threshold value 75. And hence the connected edges are more prominent.

E. Classification of Split μ and μ jump

Split μ roads have the coefficient of friction values significantly different between the left and the right wheel path. They are identified by dividing each frame into two equal halves and the concepts like edges, contours, Hough transform and histogram are applied to both the divided frames. The total number of edges, total number of contours and the total number of pixels count found from the histogram technique are reduced to approximately half of the values computed from the entire frame. When the decision of the road surface taken by the divided frames is different, then it is split μ.

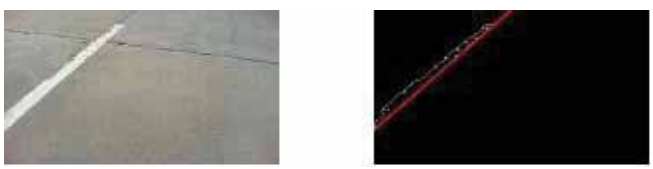
Whenever there is a transition from one surface to another surface, then it is μ jump. The transition can be from a surface having low coefficient of friction (rough) to a surface having high coefficient of friction (smooth) or vice versa. The former is positive μ jump and the latter is negative μ jump.

F. Coefficient of friction values for different roads

Once the surface is detected the μ values are also given out for various kinds of road surfaces as in Table I [6]

TABLE I COEFFICIENT OF FRICTION

Surface	μ values
Asphalt	0.65
Cement	0.75
Sand	(0.5 – 0.7)
Grass	0.35
Rough	0.20



(a) (b)

Fig. 1 (a) Cement road with lane mark, (b) lane mark identified on Figure 1.(a)

Fig. 2 Asphalt road

Fig. 3 Rough Asphalt Road

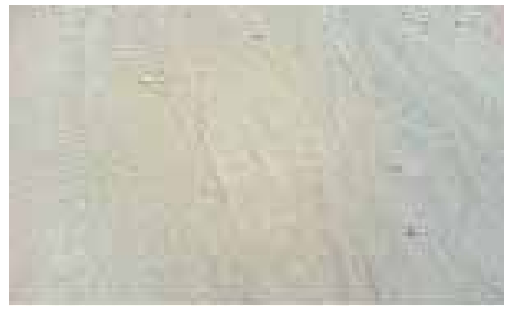


Fig. 4 Sand road

Fig. 5 Rough road

Fig. 6 Grass road

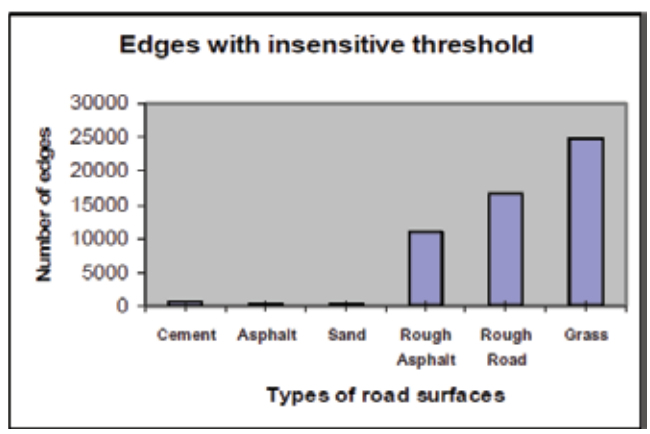


Fig. 7 Edges with insensitive threshold value for different types of road surfaces

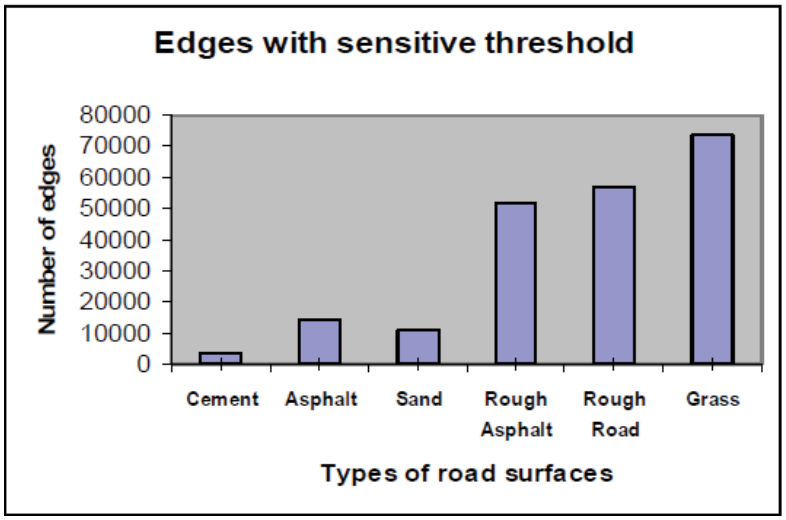


Fig. 8 Edges with sensitive threshold value for different types of road surfaces

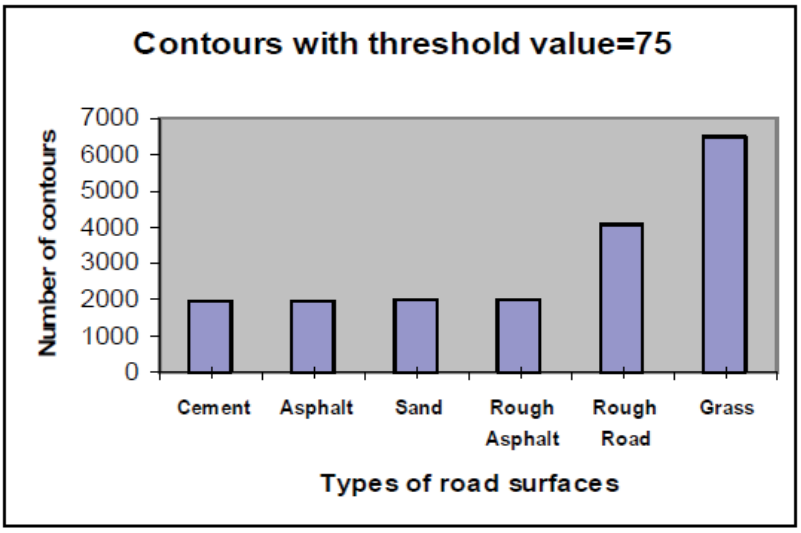


Fig. 9 Contours with threshold value of 75 for different types of road surfaces

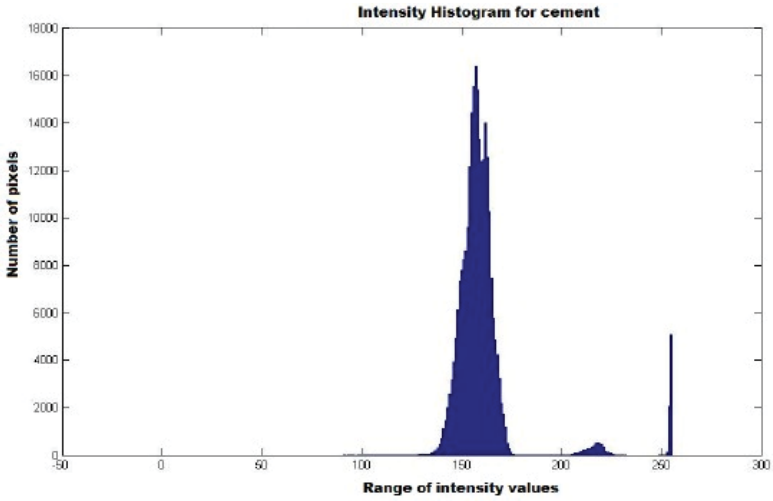


Fig. 10 Intensity histogram for cement

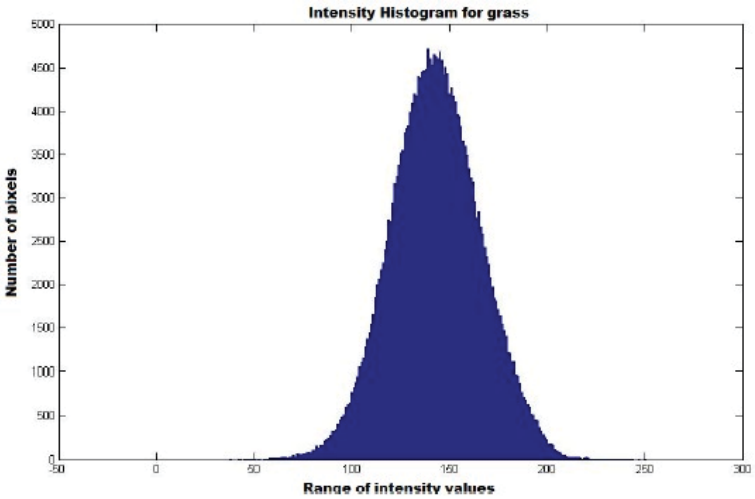


Fig. 11 Intensity histogram for Grass

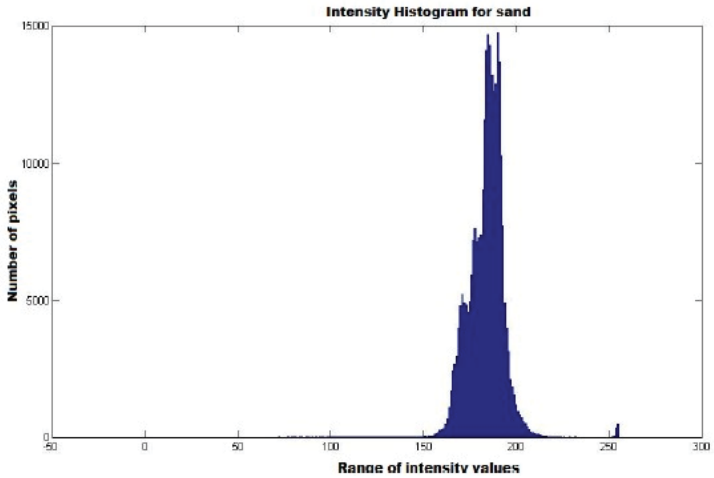


Fig. 12 Intensity histogram for Sand

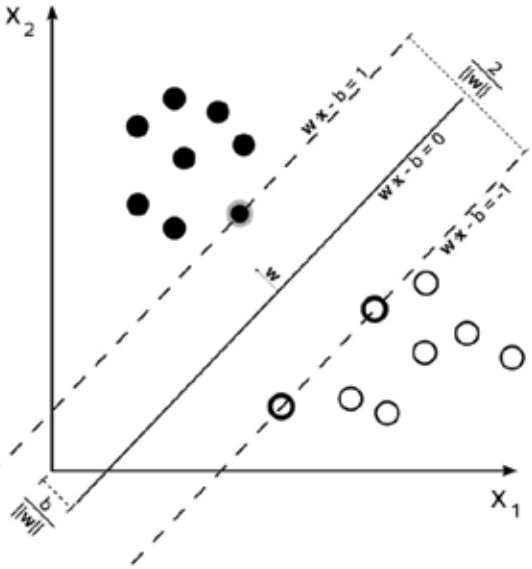


Fig. 13 Margins for an SVM trained with samples

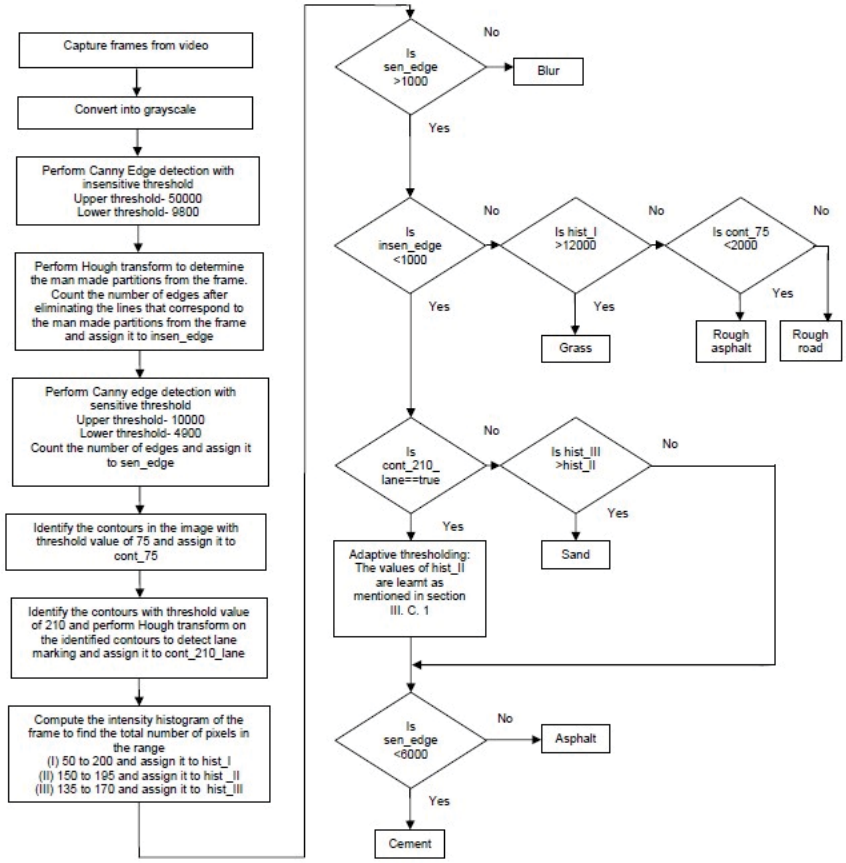


Fig. 14 Flow chart for the proposed Algorithm

The stopping distance of the ABS has been reduced based on the result of the algorithms.

TABLE II RESULTS OF THE ALGORITHM

Video Type	Stopping Distance existing technique	Stopping Distance using SVM ()
Cement 8	8.23 9	8.32
Asphalt 9	2.59 9	9.64
San 9	6.80 9	9.89
Rough asphalt 8	2.50 9	7.62
Rough	98.94	99.92
Gras 7	6.31 9	5.20

TABLE III ACCURACY RESULTS OF THE ALGORITHM

Video Type	No of fram es	True Positives	Accura cy
Cement	85	75	88.23
Asphalt	54	50	92.59
San	470	455	96.80
Rough asphalt	400	330	82.50
Rough	95	94	98.94
Gras	76	58	76.31

IV. RESULTS AND DISCUSSION

Streaming video of the road surface ahead of the vehicle was acquired by the camera mounted on the hood of the car. This streaming video was processed by the algorithm to detect and classify various road surfaces simultaneously. Table II shows the stopping of the ABS for classification of different kinds of road surfaces. Table III shows the accuracy of the algorithm for classification of different kinds of road surfaces. For example, if 85 frames are of type cement as referred in Table III, 75 frames were detected correctly and rest were either blurred or were wrongly detected. Thus a significant level of accuracy was achieved through the developed algorithm.

In future, it can be extended for night conditions as well, by providing infrared cameras for surface detection. Further this algorithm can be improved if detection of surfaces such as ice, snow and water can be done based on the specularity of such surfaces.

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