

Road Condition Classification for Driver Assistance System

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Abstract

Advance driver-assistance systems(ADAS) area system that helps the driver in the process of driving. These systems are designed to increase vehicle safety more generally road safety. Prior data about road surfaces can enhance the performance of automotive systems when a automobile is about to touch. Our paper represents an efficient techniqueto detect different surfaces of road by streaming video from a camera mounted on a vehicle's hood and compare the results with the existing process. The road surfaces taken for detection and analysis are cemented,grassy, asphalt,rough asphalt (asphalt road which is deteriorating), sandy and rough road. In this paper a classifier (Naive Bayes classifier) is used to differentiate between smooth road and rough road with the help of two new proposed features i.e. temporal distance and temporal Spread. To classify different types of roads from smooth road and rough road intensity histogram and canny edge detection is used.

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1 Introduction

Advance driver-assistance systems (ADAS) are framework to help driver in the driving process. In past many works were done in classifying different road surface areas.[1-4].Image processing techniques like canny edge detection, histogram analysis were applied for classification. They have classified the road surfaces into two broad categories: smooth road and rough road. Cement, sand and asphalt road are considered as smooth road where as grass, rough asphalt and rough road are considered to be rough road. They have considered edge as the only parameter to distinguish between smooth and rough road

surfaces. Their algorithm also does not work with a blurred frame which is quiet common in a video taken from a moving vehicle. This paper proposed a novel approach to overcome the greatest difficulty which arises due to blurring of an image taken by a camera attached on a moving vehicle's hood. Instead of taking a single frame to take the decision of smooth and rough road by computing edges only, we analyzed the temporal characteristics of road surfaces and proposed two new features [5]. With the help of a probabilistic classifier the road surfaces are classified as smooth or rough roads. The algorithm is robust as it does not make a problem even if a blurred frame

is encountered. The proposed algorithm works only in intensity plane only which makes it free from complexity [6].

The organization of the paper is as given below. Section 2 contains the road surface analysis. In this section the temporal characteristics of the road surfaces is examined followed by feature selection. This section also contains some different analysis of road surfaces. In section 3 the probabilistic approach of difference between road surfaces is discussed. Section 4 describes all the simulation result and concludes the paper.

2 Road Surface Analysis

Advance road surface information, a vehicle may experience that enhance automotive systems execution. In this proposal, an algorithm is formed that identifies distinctive road surfaces using a camera's moving video. The road surfaces recognized are smooth (asphalt, cement, sand) and rough (rough asphalt, grass and rough road) in the piece of work. Feature extraction is a critical stage for any classification problem. One needs some discriminatory features to arrange between different classes.

2.1. Temporal pixel intensity waveform analysis

Feature extraction is a vital stage for any classification issue. One needs some oppressive components to characterize between different classes. Rather than taking a symmetry waveform to recognize smooth and rough road, a gathering of casings is taken and the transient force wave type of various areas are investigated. It is found that the varieties of smooth roads are more cantabile in nature in contrast with rough road (the figure is clarified in the following chapter). Since intensity variety of smooth and rough roads fluctuates by the symmetry of waveform, the accompanying two components were proposed. i.e. temporal Distance and temporal spread. In this step, we take temporal waveform of some continuous frames from different types of videos.

From that we figured temporal distance and temporal spread of high movement blurred frames. So that misdetection of blurred frames can be kept away [7-8].

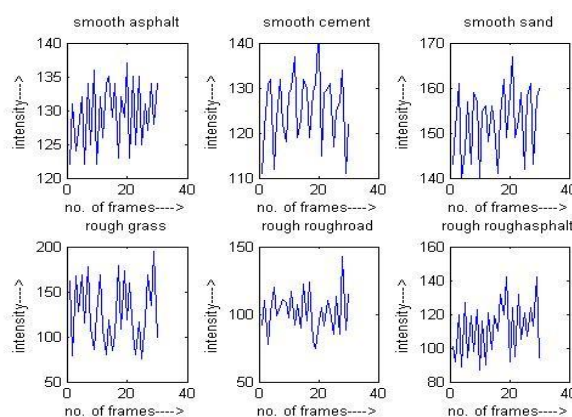


Fig. 1. Temporal frames for different types of road.

Temporal distance:

A small threshold value limits the difference between the maximum and minimum pixel intensity waveform in the temporal waveform.

$$R(x, y) = \max(PI(x, y)) - \min(PI(x, y)) \quad (1)$$

Temporal spread:

Absolute difference in the standard deviation of the pixel frequency waveform above and below mean is defined by a small value in the temporal wave form.

$$\text{spread asymmetry}(x, y) = |A - B| \quad (2)$$

$$A = \text{stddev}(PI(x, y) / pl(x, y) > c)$$

$$\text{Where, } B = \text{stddev}(PI(x, y) / PI(x, y) < c)$$

$$C = \text{mean}(PI(x, y))$$

Where $PI(x, y)$ is the pixel intensity in l th frame at position (x, y) .

2.2. Intensity histogram analysis

There are 256 different possible intensities for an 8-bit grayscale image, and the histogram will display 256 numbers graphically displaying the pixel distribution among those grayscale values.

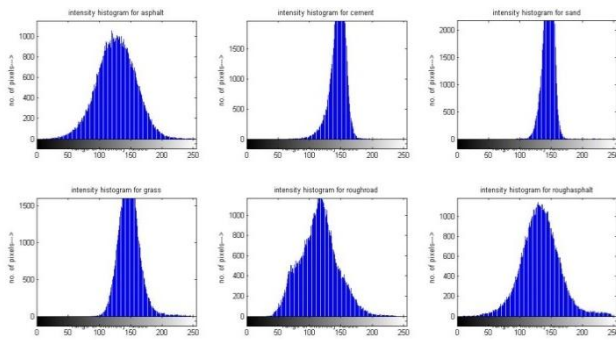


Fig. 2. Different types of road Histograms

2.3. Edge analysis

Morphological operators are used for different road. Sum of edges of smooth road are more than the rough road. X-axis depicts road surface types and Y-axis for sum of the edges. On the basis of edges we can distinguish between cement and asphalt.

The morphological operations are used for edge detection. The steps are as follows:

1. The image is captured and converted into grayscale.
2. The image is further transformed into structuring components. All structuring elements are linear in form and/or might be line-based flat.

For the dilation and erosion operations, different structuring components were selected. A division angle of n that is used for quantitative analysis has been considered. A gray scale structuring component $B(s, t)$ indicates the erosion of gray scale image $I(x, y)$

$$I \ominus S = \min_{[i,j] \in B} \{a[m-j, n-k] + b[j, k]\} \quad (3)$$

3. The picture is under the dilation and erosion process. Dilation of a grey-scale image $I(x, y)$ through a grey-scale structuring element $S(s, t)$ is indicated by

$$I \oplus S = \max_{[i,j] \in B} \{a[m-j, n-k] + b[j, k]\} \quad (4)$$

4. Find the edges for various structuring elements using the morphological operator.

$$Edge(I) = (I \oplus S) - (I \ominus S) \quad (5)$$

5. MSE and PSNR were then evaluated for various structuring elements as

$$PSNR = 10 \log(255^2 / MSE) \quad (6)$$

Gray-scale image $I(x, y)$ opening and closing by gray-scale structuring element

$B(s, t)$ are denoted respectively by

$$\begin{aligned} A \circ B &= \\ (A \ominus B) \oplus B & \end{aligned} \quad (7)$$

$$A \cdot B = (A \oplus B) \ominus B \quad (8)$$

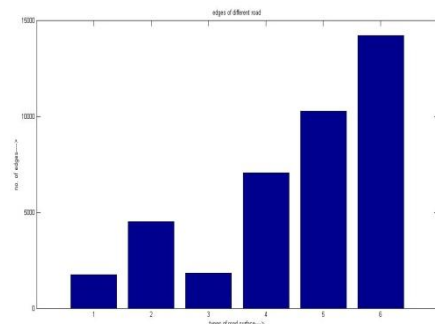


Fig. 3. Edge boundary for different types of road

3 Road Surface Detection

In vision based surface detection for car framework there are numerous sorts of issues, for example, we can't distinguish sand road as smooth road in light of the fact that there are numerous imprints that produce by man, creatures, and vehicles may bring about such path marks. Because of path imprints edge will be more. When contrasted with smooth road edge must be not as much as rough road. Here and there sand road can't be recognized as smooth road. When we take a video of a road for some span during high movement of vehicle, there must be some blurred

frame. From that we can't get any data about the road surfaces for further investigation. To overcome these issues we can utilize a classifier so that most importantly we can recognize rough road from smooth road. Since we have taken a few variables in classifier (testing) we recognize rough road from smooth road. So we can get a thought regarding the road before going to any assessment. What's more, to overcome about blurred frames we have taken temporal waveform. With the goal that we can recognize intensity of some continuous frames, so there is no burden about one frame or blurred frame.

3.1 Naïve Bayes classifier

Bayes hypothesis provides an immediate strategy to determine the likelihood of a hypothesis given its earlier likelihood, the possibility of observing different data given the hypothesis, and the data itself observed. Naive Bayes is a probabilistic algorithm for machine learning that can be used in a wide range of classification tasks. Typical applications include filtering spam, sentiment prediction, classifying documents, etc. It is based on Rev. Thomas Bayes' works (1702–61). Because it is a probabilistic model, it is easy to encode the algorithm and the predictions made it really fast. It is therefore easily scalable and is traditionally the algorithm of choice for real-world applications (apps) that are expected to respond instantly to user requests. Naive Bayes is a sort of classifier that uses the theorem of Bayes. This estimates membership probabilities for each class, such as the likelihood that a particular class belongs to a given data point or record. The highest likelihood class is considered to be the most likely class. This is also referred to as Maximum A Posteriori (MAP). Naive Bayes can be used for the classification of binary and multiclass. This offers various types of Naive Bayes algorithms such as MultinomialNB, GaussianNB, BernoulliNB. It is a simple algorithm that depends on a bunch of counts being completed. Great choice for problems with text

identification. It's a popular choice to classify spam email. Bayes theorem provides a way to calculate $P(c|x)$ from $P(x)$, $P(c)$ and $P(x|c)$ posterior probability. Given below a following equation:

$$P_r(c/x) = \frac{P_r(x/c)P_r(c)}{P_r(x)}$$

(9)

$$P_r(c/x) = P_r(x_1/c) \times P_r(x_2/c) \times \dots \times P_r(x_n/c) \times P_r(c)$$

(10)

- $P_r(c/x)$ is the posterior class probability (c , target) given predictor (x , attributes).
- $P_r(c)$ is the prior class probability.
- $P_r(x/c)$ is the likelihood which is the predictor given class probability.
- $P_r(x)$ is the prior predictor probability.

3.2 Histogram and edge detection

Histogram is mainly a diagram showing the pixels quantity contained in the image at each diverse intensity value found in that image. There are 256 different conceivable intensities for an 8-bit grayscale image, so the histogram will graphically display 256 numbers showing pixel dissemination among those grayscale values. In a more basic manner to clarify, a histogram is a visual chart, whose X-axis speaks to the tonal scale (dark at the left and white at the privilege), and Y-axis speaks to the quantity of pixels in a picture in a specific zone of the tonal scale. For instance, the diagram of a luminance histogram demonstrates the quantity of pixels for every splendor level (from dark to white), and when there are more pixels, the top at the specific luminance level is higher [9]. Here we have utilized canny edge detection [10-11] for distinguishing the edges. It is watched that the number of edges shifts essentially for asphalt and cement roads. A threshold value of edge is processed by watching the quantity of edges. Here we found the threshold value of edges is 14000.

4 Simulation Results

All the simulations are done in MATLAB 7.12.0 environment. Temporal distance & Temporal waveform of different Roads Temporal distance and temporal spread are proposed from temporal waveform which is two basic features of Classification between smooth road and rough road. Here this graph shows 2 features of Asphalt Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples are somehow equal but in feature 2 fluctuations of samples are more than feature 1.

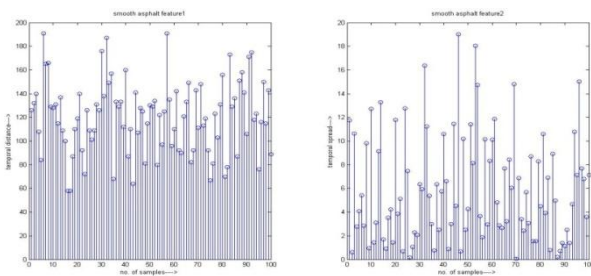


Fig.4. 2 Features of Cement Road

In Fig. 4 graph shows 2 features of Cement Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples is somehow equal but in feature 2 fluctuations of samples is more than feature 1.

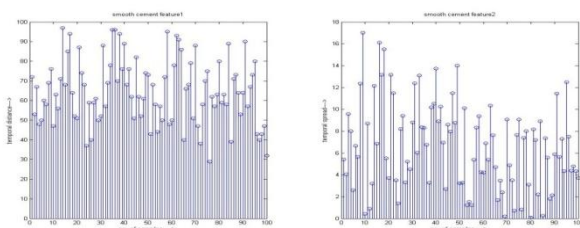


Fig.5.2 Features of Sand Road

Here this graph shows 2 features of Sand Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples is somehow equal but in

feature 2 fluctuations of samples is more than feature 1.

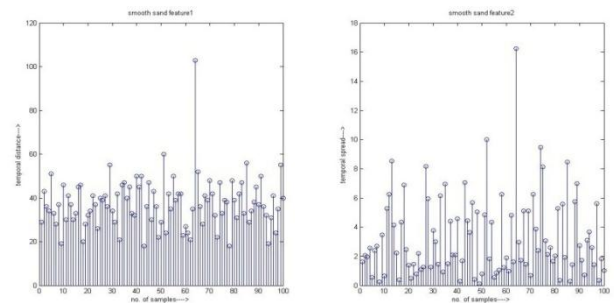


Fig.6. 2 Features of Grass Road

Here this graph shows 2 features of Grass Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples is somehow equal but in feature 2 fluctuations of samples is more than feature 1.

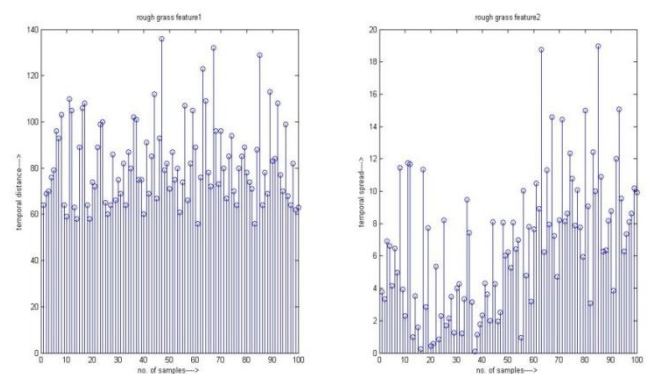


Fig.7. 2 Features of Rough Road

Here this graph shows 2 features of Rough Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples is somehow equal but in feature 2 fluctuations of samples is more than feature 1.

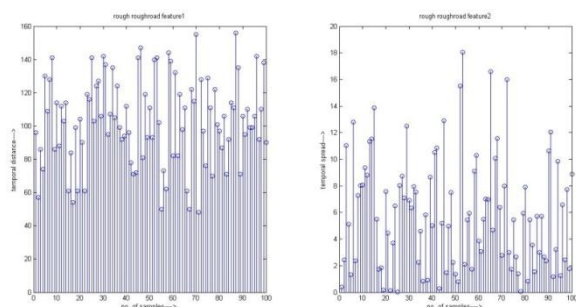


Fig.8. 2 Features of Rough Asphalt Road

Here this graph shows 2 features of Rough Asphalt Road. Here in the graph in X-axis no. of samples are taken and in Y-axis temporal distance and temporal spread are taken. In feature 1 the variation of samples is somehow equal but in feature 2 fluctuations of samples is more than feature 1.

Classification of Roads

Here we take some window size according to correctly and falsely classification of frames as smooth and rough. And in this table, we take temporal window size 9 and values are obtained which is not given satisfaction properly.

Table 1.Temporal window size=9

| Roads | No. of Frames Tested | No. of Frames classified as Rough | No. of Frames classified as Smooth |
|----------------------|----------------------|-----------------------------------|------------------------------------|
| Asphalt(Smooth) | 60 | 8 | 52 |
| Cement(Smooth) | 60 | 9 | 51 |
| Sand(Smooth) | 60 | 10 | 50 |
| Grass(Rough) | 60 | 49 | 11 |
| Rough Road(Rough) | 60 | 48 | 12 |
| Rough Asphalt(Rough) | 60 | 48 | 12 |

Here we take some window size according to correctly and falsely classification of frames as smooth and rough. And in this table, we take temporal window size 11 and values are obtained which is more accurate than window size 9. So, we take these values for further analysis.

Table 2.Temporal window size=11

| Roads | No. of Frames Tested | No. of Frames classified as Rough | No. of Frames classified as Smooth |
|----------------------|----------------------|-----------------------------------|------------------------------------|
| Asphalt(Smooth) | 60 | 5 | 55 |
| Cement(Smooth) | 60 | 7 | 53 |
| Sand(Smooth) | 60 | 4 | 56 |
| Grass(Rough) | 60 | 51 | 9 |
| Rough Road(Rough) | 60 | 50 | 10 |
| Rough Asphalt(Rough) | 60 | 49 | 11 |

Here this table shows the differentiation of 3 types of basic smooth road from smooth road on the basis of classification according to proposed 2 features which are described before.

Table 3.Classification of Smooth Road

| Roads(Smooth) | No. of Frames Tested | No. of Frames correctly classified | No. of Frames falsely classified |
|---------------|----------------------|------------------------------------|----------------------------------|
| Asphalt | 60 | 47 | 13 |
| Cement | 60 | 49 | 11 |
| Sand | 60 | 55 | 5 |

Here this table shows the differentiation of 3 types of basic rough road from rough road on the basis

of classification according to proposed 2 features which are described before.

Table 4.Classification of Rough Road

| Roads(Rough) | No. of Frames Tested | No. of Frames correctly classified | No. of Frames falsely classified |
|---------------|----------------------|------------------------------------|----------------------------------|
| Grass | 60 | 46 | 14 |
| Rough Road | 60 | 50 | 10 |
| Rough Asphalt | 60 | 53 | 17 |

Here the table shows truly positive and also accuracy between both algorithms. In some cases, their result is more accurate and some others, proposed result is more accurate.

5 Conclusion

It can be linked in the future for night conditions by giving surface discovery to infrared cameras. Likewise, this calculation can be enhanced if identification of objects, such as ice, water and snow should be possible given the secularity of such surfaces. This strategy will upgrade the car framework by providing the vehicle with impelled road information. Using data about the edge and location of the camera inside the surrounding edge detection techniques of the car, the breakpoint could be altered on both sides of the road before using an image for area purposes. This would remove the interest from the environment and improve the gathering of results in the same way. Recognizable edge could be used to uncover the track and focus secured parts on a photo. Alternate sections could then be rearranged to enable proof on those fragments of the true condition of the lane. In any case, this can only be achieved with better picture data determination.

References

[1] John Canny," A Computational Approach to Edge Detection". IEEE transactions on pattern analysis

and machine intelligence, vol. pami-8, no. 6, november 1986

[2] Bin Yu and Anil K. Jain," Lane Boundary Detection Using A Multiresolution Hough Transform".Dept. of Computer Science, Michigan State University, East Lansing, MI 48824-1997

[3] Kenshiro Hashimoto, Shigeto Nakayama, Tohru Saito, Shinnosuke Ishida, KiyozumiUnoura, Jun Ishii, Nobuyuki &no, Yasusi Okada," An Image processing Architecture and a Motion Control Method for an Autonomous Vehicle. HONDA RLD Wako Research Center.-2005

[4] Maria Jokela&MattiKutilla& Long Le," Road Condition Monitoring System Based on a Stereo Camera". VTT Technical Research Centre of Finland,IEEE Edition-2009.

[5] Behera, S., & Mohanty, M. N. (2012). Land boundary detection of an island using improved morphological operation. International Journal of Image Processing (IJIP), 6(6), 413-421.

[6] Behera, S., Mohanty, M. N., & Patnaik, S. (2012). A comparative analysis on edge detection of colloid cyst: A medical imaging approach. In Soft Computing Techniques in Vision Science (pp. 63-85). Springer, Berlin, Heidelberg.

[7] Kar, S. K., & Mohanty, M. N. (2013, January). Statistical approach for color image detection. In 2013 International Conference on Computer Communication and Informatics (pp. 1-4). IEEE.

[8] T. Anbalagan, C. Gowrishankar, Dr. A. Shanmugam," SVM Based Road Surface Detection to Improve Performance of ABS". Journal of Applied Sciences Research, 9(1): 104-112, 2013

[9] Jyoti, A., Mohanty, M. N., Kar, S. K., & Biswal, B. N. (2015). Optimized clustering method for CT brain image segmentation. In Proceedings of the 3rd International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014 (pp. 317-324). Springer, Cham.

[10] Arjun Raj, Dilip Krishna, HariPriya. R, Kumar Shantanu, Niranjani Devi. "Vision based Road Surface Detection for Automotive Systems". Engineering Services for Active Safety – Customer Projects Robert Bosch Engineering and Business Solutions (RBEI) Coimbatore, India

[11] R.C. Gonzalez, R.E. Woods and S.L. Eddins: "Digital Image Processing using MATLAB", Pearson Education Inc.,3rd Edition,2009.