Speed Breaker Detection Using GLCM Features

M.Bharathi, A.Amsaveni, B. Manikandan

Abstract: Road accidents are increasing worldwide, that leads to death, injuries and vehicle damages. Most of the accidents happen due to the improper warning sign and unnoticeable speed breakers on the road especially during night. Identification and notification of road signs and speed breakers to the driver at proper time is very important to avoid accidents. In this paper, speed breaker identification using Gray Level Co-occurrence Matrix (GLCM) features is proposed. This method has three stages namely pre-processing, feature extraction and classification. Noise removal, Resizing the image and gray scale conversion has been done as a part of pre-processing. In the feature extraction step, the spatial relationship between the pixels is obtained. GLCM features are the second order statistical features of the image. These features includes correlation, Angular Second Moment, Entropy, Homogeneity and contrast. In this paper, features are consider as the shape, texture and feature statistics. Neural Network based classifier is used in the third stage to identify the presence of speed breaker. The performance of the classifier is evaluated by calculating the confusion matrix.

Keywords: speed breaker, image processing, GLCM, feature extraction.

I. INTRODUCTION

Vehicle over speed is one of the major factors for road accidents. To control speed in sensitive areas speed breakers are used across the road. Thus speed breakers are mainly used to reduce the vehicle speed and improve the pedestrian's safety. However, in case of driver not noticing the speed breaker well in advance leads to injuries, vehicle damage and casualties. Due to the high vehicle speed, the presence of speed breakers on the national highways is a major problem. Many unauthorized speed breakers are laid on the road which does not follow the standard size proposed by National Highway Authorities. Generally, the speed breakers are of width 9 meters with the height ranging from 6 to 30cms [1]. Apart from speed breakers, potholes, mud pits, and garbage are some of the common problems on the road which creates hindrance for the traffic. Different speed levels are set based on aspects of types of roads and speed breakers. Due to the vehicle movement, the detection must be quick to warn the drivers before hitting the speed breaker. A survey report records that in India totally 1, 42,485 people were died due to road accidents [2]. According to Road Transport and Highway ministry of India, because of accident 4746 injuries occurred due to speed humps, 6672 people died due to potholes and speed breakers [8]. Reducing road accidents is possible by proper monitoring of road anomalies like speed bump and potholes.It is necessary to have a driver support system with speed breaker detection in the vehicle to inform the driver about the approaching speed breakers well in advance.

Various methods are proposed in the literature for the detection of speed breakers using dedicated hardware such as 3-axis accelerometer and GPS [1-4]. Road condition detection with the help of smart phones and image processing[28] techniques are also proposed. Fernandez and W. Zhang [1, 2] proposed forward looking LIDARs and cameras to detect the speed breakers on the road. LIDAR based road and road edge detection algorithms were developed to identify the region of interest. Hull [3], in his works proposed a Distributed Mobile sensing system named "CarTel" for various applications including Traffic monitoring, Speed breaker detection etc. For speed breaker detection, this system has centralized software to collect, process, deliver, and visualize data from vibration sensors located on vehicle. All the details about the road conditions will be maintained in a centralized location. The data from the centralized location will be accessed by the applications using continuous queries, which are executed using a Delay-tolerant continuous query processor. A similar system called "Pothole Patrol" was proposed by Jakob Eriksson [4] for road surface monitoring. The condition of the road is gathered using Vibration sensors and GPS. Machine learning algorithms are used to process the gathered data and to detect the anomalies on the road.

Detection of road conditions using smart phones [5-14] is gaining interest in the recent past due to the increase in the number of smart phone users. Mohan [6], in his work discussed Nericell, a system that monitors road conditions and detect the speed breakers using accelerometer, microphone, GSM Radio and GPS sensors that are available in smartphones. However, in smartphone based method, the orientation of the phone with the direction of motion is very important. Thus, before accelerometer measurement is done, it is vital to virtually reorient the accelerometer with respect to the vehicle. Heuristics based method is used in Nericell for road condition monitoring. The main drawback of Nericell system was addressed by Ravi Bhoraskar [7], in his proposed system "Wolverine" In this system magnetometer was used to find the horizontal orientation of the phone instead of visual reorientation. In Wolverine method K-means clustering and Support Vector Machine (SVM) was used for determining the traffic and road conditions. Accelerometers in the android-based mobile phones [8, 9] are used to collect the information about the road which is then analyzed to understand the condition of the road. This information are stored in a server and helps in educating the drivers about the road conditions.

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Vamsee has proposed a real-time solution [10] using android service that runs in the background and relies on Google Mapsapplication in the smartphone. This service will give an early warning to the driver in case of a speed breaker or a bumpy road. Although a lot of effort has been put to develop a system using smart phones, there are certain limitations which includes vibration pattern of sensor data, GPS Error, Network overload, Delay and Battery draining problem. These limitations make it difficult to use smartphones for real time road condition detection.

BUMPSTER, a mobile cloud computing system for speed breaker detection was proposed by ArhumSavera [15]. In this work data from different places are collected and stored in cloud and support vector machines are used to warn the driver ahead of the approaching speed breakers. Driver assistance system using Image processing algorithms [16-18] were proposed in the literature. In [16, 17], speed breaker detection using edge detection and morphological image processing were discussed. AjitDanti [18], in his work proposes automatic [26] driver assistance system. In this work, Hough Transformation is employed for Lane detection, Color Segmentation [27] and Shape Modelling with Thin Spline Transformation (TPS) is used with nearest neighbour classifier for road sign detection and Classification. Further, K-means clustering based algorithm is used for pothole detection. Speed breaker detection using BLOB analysis was explored in [25].

In this work, GLCM features are used to identify the presence of speed breakers and inform the drivers about the approaching speed breaker. Overview of the proposed method with the details of each block is discussed in chapter 2. The performance analysis of this method is discussed in chapter 3 and chapter 4 provides the conclusion.

II. PROPOSED METHODOLOGY

GLCM features are the second order statistical features of the image. GLCM feature operator provides a virtual variable to represent a texture feature. GLCM features includes area, entropy, eccentricity, homogeneity, correlation, dissimilarity etc.,

The steps of the proposed method is given in Fig.1. Real time image of the road is obtained using a camera mounted in the front of the vehicle. Noise removal, image Resize, RGB to Gray conversion are the operations carried out in step 1. GLCM features are extracted from the pre-processed image in step 2 and neural network based classifier is used to detect the presence of speed breaker from the GLCM features.

A. Pre-processing

In the pre-processing stage, median filter is used to smoothen the image. The image is resized to a standard size of 256 × 256 pixels. As processing of colour image is complex and also luminance is the important parameter in distinguishing the visual feature, the RGB colour image is converted to gray scale image

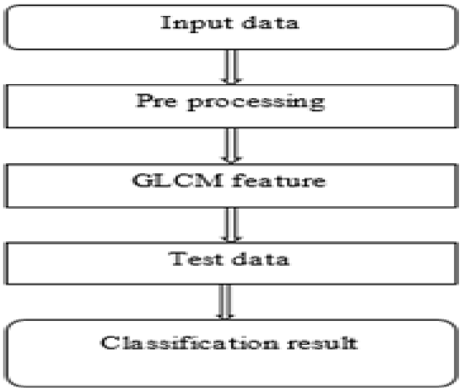

Fig.1.Speed breaker detection using GLCM features.

The luminance value of the gray scale image is given by

$$L(x, y) = 0.21R(x, y) + 0.72G(x, y) + 0.07B(x, y) \qquad (1)$$

Where, R-Red element of the image
G-Green element of the image
B-Blue element of the image
x,y-Position of a pixel
Images at different stages of pre-processing are given Fig 2.

(a) (b)

Fig.2. Stages of Pre-processing
Resized Image (b) Gray scale Image

B. Feature extraction

A feature represents the important information that would be used for solving computational task related to specific application [19]. Feature extraction is used to reduce the dataset by certain features which means by reducing the number of resources. A large number of variables are required for a large amount of memory and computation process [20].Generally, feature extraction is described in terms of a combination of variables and also used for accurate classification of images. GLCM is the statistical distribution of a combination of intensity at the specified position relative to each image. GLCM is the second order statistical texture feature. In image processing and pattern recognition, feature extraction is the important step, which is used for dimensionality reduction. When the input is a large set of data to be processed and assumed to be redundant then it will be transferred to a reduced set of feature representation. The transformation of input into a set of feature representation is called the feature extraction.

C. Gray level co-occurrence matrix:

The identification of texture image is done by two dimensional gray level variation which is called as gray level co-occurrence matrix [21]. GLCM method is the statistical method which is used to estimate the image properties related to second order statistics. GLCM method used to relate to two neighboring pixels, where the first pixel is called reference pixel and the second pixel is called neighbor pixel. A co-occurrence matrix is referred to an occurrence of distribution over an image. The occurring values at a given offset to be represented as distance and angular spatial relationship over an image. GLCM of an image is calculated by using the expression

$$G_{(\Delta x,\Delta y)}(i,j) = \sum_{p=1}^{M}\sum_{q=1}^{N} 1\{I(p,q) = i\} and\ 1\{I(p+\Delta x, q+\Delta y = j \qquad (2)$$

$I(p,q)$-gray value pixel at p's rows and q's column
i,j-gray values
Δ_x, Δ_y-positional offset in x and y direction
M, N-number of rows and columns of the image

The second-order gray level probability distribution of a texture image can be calculated by using gray levels of pixels in pairs at a time [18].The original image pixel value shown in Fig.3. From the image pixel expose the feature at different direction such as 0°, 45°,90°,135° [22].

1	1	3	6	3
2	3	5	7	1
4	5	7	1	2
3	5	1	2	3

Fig.3 Original image pixel value

The0° direction of the features shown in the Fig.4.Each feature value extracted by the forward direction of the original image at range 1to 1 and 1 to 2.

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Fig.4.GLCM in 0^°direction

A co-occurrence matrix describes the joint probability of gray level of image pixel value which form of a matrix with the dimensionN_gXN_g a pair of gray level points separated by two displacement vector.

$$p_d(i,j) = \left|\{((r,s),(r+dx, s+dy)) : I(r,s) = i, Ir+dx, s+dy = j \right| \qquad (3)$$

$p_d(i,j)$- set of pair of points
(i,j)- Gray level values
(dx,dy)- Displacement vector

The output of the 45° feature vectors shown in Fig.4. Each feature value represent the 1 to 1 and 1 to 2 at 45 degree direction from the original image.

	1	2	3	4	5	6	7	8
1	2	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	1	0	0	0	0	0
5	0	0	0	0	1	1	1	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	1	1
8	0	0	0	0	1	0	0	0

Fig.5.GLCM in 〖45〗 ^° direction

The Gray level co-occurrence matrix is the two-dimensional matrix with a pair of pixels separated by a distance and direction. While the intensity is flat, the resulting GLCM are completely diagonal. If image texture increases, off-diagonal values in GLCM becomes larger. GLCM of co-occurrence matrix is calculated for different features such as contrast, absolute value, inverse difference moment, entropy, angular second moment, energy, correlation. The GLCM features which are considered for the classification of speed breakers is given here.

D. Contrast

Contrast is used to measure the quantity of local changes in image and it changes the sensitivity of texture relation in the image. It measures the intensity contrast between a pixel and neighbourhood pixel. If contrast is 0 that would be the constant image. If the local variation is large, the contrast feature is higher. If the grayscale difference occurs continuously, the contrast becomes large. If the texture becomes critical, the contrast value would be small. Contrast has difference moment of order 2.In real world, Contrast is calculated by the difference between color and brightness of the object.

$$\text{Contrast}=\sum_i \sum_j (i-j)^2 C_{ij}$$

E. Homogeneity

Homogeneity measures the similarity of a pixel. A diagonal matrix gives the homogeneity of 1.homogenity becomes large if the local texture has the minimal value [23].

$$\text{Homogeneity}=\sum_i \sum_j \frac{p_{d,\theta(i,j)}}{1+|i-j|}$$

F. Energy

When all co-occurrence matrix is equal. Energy can be defined as the sum of squared elements in GLCM. It used to measure the repetition of a pair of pixel and uniformity of the image. While the energy is equal to 1, it should be a constant image. Energy value should be high

$$\text{Energy}=\sum_i \sum_j p^2(i,j)$$

G. Entropy

Entropy is used to measure the loss of information and also using the image compression technique. It measures the randomness of gray levels in the image. The entropy is small when the image is texturally uniform [19].

$$\text{Entropy}=-\sum_i \sum_j P(i,j)log[P(i,j)]$$

H. Correlation

Correlation measures the neighbouring pixel value of gray level with linear dependency over the whole image. Correlation indicates the range from -1 to 1 which explains the perfect positive and negative values. It is also used for measuring the deformation and displacement of the pixel [20].

$$\text{Correlation}=\sum_i \sum_j \frac{(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$$

I. Inverse difference moment

Inverse difference moment defines a measure of image texture and local homogeneity of the image. Features are achieved by means of measuring the closeness of the distribution to the diagonal elements. For getting high value, the local gray should be uniform and inverse GLCM uniform should be high. Inverse difference moment value is calculated by whether the image is textured or non-textured.

$$\text{Inverse difference moment}=\frac{\sum_i \sum_j P_{ij}}{1+(i-j)^2}$$

J. Angular second moment

Angular second moment measures the uniformity of grayscale distribution and homogeneity. The angular second moment is high when the image was good homogeneity.

$$\text{Angular second moment}=\sum_i \sum_j P_{ij}^2$$

III. RESULT AND DISCUSSION

The Gray Level Co-occurrence Matrix (GLCM) features extracts the Statistical Texture Parameters. The GLCM features considered for this classification are autocorrelation, contrast, energy, entropy, homogeneity, dissimilarity, Inverse difference moment, Sum average, Sum entropy. For different images these values will be different. The classifier neural network is trained using the GLCM feature of the training set. The trained network is used to classify the real time images. The output of the classifier for two classes of images are shown in Fig.6a and Fig.6b.20 images are given to network for speed breaker detection method.

Fig.6.a.Output of the classifier for image with speed breaker

Fig.6.b. Output of the classifier for image without speed breaker

Confusion matrix is the table used to check the performance of the classifier for training, validation, and testing data sets. The confusion matrix of the speed breaker classifier is shown in Fig7. The confusion matrix has four parameters True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP and TN specifies the correct classification and FP and FN gives misclassification. The tabular form of confusion matrix is given in Table.1.

Fig.7. confusion matrix for speed breaker detection

Category	True positive (%)	True negative (%)	False positive (%)	False negative (%)
Training	35.7	57.1	0	7.1
Validation	66.7	0	0	33.3
Testing	0	33.3	0	66.7
Overall	35	45	0	20

Table 1.Different category of confusion matrix output

The data set contains 20 images out of which 11 were with speed breaker and 9 without speed breaker. Table 2 shows the range of GLCM features for images with speed breaker and Table 3 shows the GLCM features for images without speed breaker.

Sensitivity and Specificity are the statistical measures used to analyze the performance of the classifier. These parameters are calculated using TP, TN, FP and FN. Sensitivity represents the capability of the system to analyze the images without speed breaker. Specificity represents the capability of the system to diagnose the speed breaker correctly.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The sensitivity, Specificity and accuracy of the proposed method is tabulated in Table 4.

Images	autocorrelation	contrast	energy	entropy	homogeneity	dissimilarity	Inverse difference moment	Sum average	Sum entropy
1	25.1895	0.4197	0.0868	2.7279	0.9026	0.2373	0.9941	8.9757	2.4779
2	25.0470	0.6537	0.0714	2.9432	0.8558	0.3523	0.9911	8.9852	2.5919
3	25.1783	0.3954	0.0880	2.6874	0.9007	0.2350	0.9945	8.9655	2.4392
4	25.3443	0.5089	0.0843	2.7908	0.8946	0.2667	0.9930	9.0094	2.4869
5	25.1961	0.5793	0.0854	2.7606	0.8946	0.2789	0.9921	9.0000	2.4670

Table 2.GLCM Features of images with speed breaker

Images	autocorrelation	contrast	energy	entropy	homogeneity	dissimilarity	Inverse difference moment	Sum average	Sum entropy
1	25.1797	0.7101	0.0719	2.9647	0.8491	0.3622	0.9904	9.0140	2.5814
2	25.2617	0.8770	0.0701	2.9907	0.8429	0.4087	0.9885	9.0363	2.5818
3	25.1548	1.3474	0.0582	3.1800	0.7928	0.5554	0.9836	9.0783	2.6363
4	25.3139	0.8967	0.0751	2.9122	0.8642	0.3620	0.9892	9.0637	2.5676
5	25.0768	0.8115	0.0673	3.0585	0.8373	0.4182	0.9888	8.9852	2.5932
6	24.9254	1.2846	0.0543	3.2461	0.7747	0.5878	0.9836	9.0238	2.6436
7	24.8240	1.2524	0.0677	3.0780	0.8347	0.4836	0.9841	8.9874	2.5818
8	25.2677	0.4705	0.0801	2.8227	0.8840	0.2727	0.9936	8.9920	2.5403
9	24.9765	0.7924	0.0662	3.0222	0.8304	0.4188	0.9893	8.9787	2.5981

Table 3.GLCM Features of images without speed breaker

True positive	True negative	False positive	False negative	Sensitivity	Specificity	accuracy
7	9	3	4	0.666	0.7272	80%

Table 4: Performance of classifier

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IV. CONCLUSION

Speed breakers are one of the major causes for accident. Automatic detection of speed breakers are important to avoid accidents. In this paper speed breaker detection using GLCM features with Neural Network classifier is proposed. The proposed method is designed for real time speed breaker detection. An accuracy of 80% is obtained using the proposed method.

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