A PERCEPTION BASED ADVANCED VIRTUAL ROBOTIC ASSISTANCE TO DRIVER FOR TRAFFIC SIGN DETECTION

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Abstract: *Now-a-days, due to the tremendous growth of vehicles, driving is become a complex and multitasking process which includes perception and cognition of drivers and motor movements. For safety concerns, the traffic signs and the vehicle information has to be displayed which strongly impacts the attention of drivers with reduced mental workloads. Drivers need some assistance to maintain their awareness and leading their attention to potential hazards. In this paper, a computer vision based technique is proposed to detect and recognize traffic signs based on their color and shape features. The investigation of traffic sign recognition has been of extraordinary attractions and the proposed system is addressed by a four phase system including segmentation, detection, feature extraction, and classification. We cover recent attempts to establish an automatic agent detect the traffic signs for vision based Driver Assistance System (DAS). We present a novel framework based on the system for recognizing circular, square, and triangular traffic signs makes utilization of artificial intelligence system, for example, heuristics functions to discover shapes. In order to prove the performance of the proposed system, the features of the detected traffic sign is given to three different classifiers such as j48, Naïve Bayes, and k-nearest neighbor (k-NN) for classification and the obtained results are tabulated. The proposed framework is established in real world scenario and tested in highways and intends for assisting vehicle driver to have more secure and pleasant driving so that focusing on his real workload.*

Key words: *Traffic signs, advanced driver assistance system (ADAS), segmentation, detection, feature extraction, classification, j48, Naïve Bayes, and k-NN.*

1. Introduction.

Advanced driver assistance system (ADAS) has gained more attention in the field of automotive electronics. This ADAS technology is used in some other fields such as vision based systems [1], active sensors systems [2], car data or vehicular networks [3], and so on. In order to extract different sorts of information, these devices are employed at the driving environments. In real outdoor scenes, the environmental understanding and vehicle guidance are considered as the most important challenges for ADAS technology. Traffic signs are established for guiding, warning, and regulating the vehicular traffic. The vehicle drivers observe some information from those traffic signs. But in reality, the drivers always may not observe the road signs. It is so hard to perceive traffic signs accurately at night time or bad weather condition and also the drivers are simply affected by headlights of oncoming opposite vehicles. These circumstances may prompt car crashes and serious damages. Thus, the vision-based road sign detection and recognition framework is attractive to grab the observation of a driver for avoiding traffic hazards.

These frameworks are essential assignments for ADAS, as well as for other real time applications like understanding of urban scene, automatic driving, or even monitoring of traffic signs for maintenance. It can improve security by notifying the drivers about the present condition of road signs over the road and providing useful information about safety measure. Nevertheless, there are several factors have made the recognition of road or traffic signs issue difficult, for example, changes of lighting conditions, distortion of signs, impediment of traffic signs because of hurdles, motion blur of video images, and so on. Generally, a traffic sign recognition technique comprises of two major phases: one is detection phase and another one is recognition phase. The detection phase obtains camera images and discovers every one of the regions in the images which may comprise road signs and the classification phase decides the type of road sign in every region of the image. The encoding of information extracted from the traffic signs is done in their visual properties such as shading, pictogram, and shape, etc. Hence, both the detection and recognition phases depend on shading and shape indications of road signs. This paper presents a fast framework for vision based road sign detection and recognition.

The traffic sign detection of camera images is done by implementing following steps such as pre-processing, image segmentation, detection and classification. Among these classification is considered as final stage and those results were considered for system efficiency. Pre-processing plays a vital role in eliminating noisy, irregular and insufficient data from an image. In this paper, pre-processing of given camera image is done with median filter to remove impulse noise without affecting the original image. Then the image segmentation is done by using morphological operations including image erosion, dilation, opening and closing. Next stage is the detection which is done by segmenting color (like red, blue, and green) and shape (like circular, square, and triangular). Then the feature extraction is performed by wavelet transform which is a powerful tool since it permits image analysis at different degrees of resolution because of its property called multi-resolution analytics. Final stage is the classification which is done with three classifiers such as j48, Naïve Bayes, and k-nearest neighbor (k-NN).

The rest of the paper is organized as follows. The section 2 discusses some existing works and the proposed methodology is explained in section 3. In section 4 result and discussion is explained and section 5 concludes the work.

2. Related Work.

Most of the existing traffic sign detection and recognition systems [4]–[5] initially discover the position of every traffic signs in the given image. To detect the road traffic signs, there are three main detection techniques are present such as color based detection, shape based detection, and both color and shape based detection. Several researchers have utilized a variety of color based detection frameworks. Ghica [6] has presented a technique which calculates the RGB space distances between the pixel and the reference colors. They utilized thresholding technique for segmenting pixels in a computerized image into object as well as background pixels.

Estevez and Kehtarnavaz [7] have proposed a framework comprising six different modules like color segmentation of color, RGB differencing, edge localization, edge detection, histogram extraction, and classification. There technique is fit for perceiving some of the warning traffic signs such as the Stop, Yield, and Do-Not-Enter signs. Shape is considered as an essential feature of traffic sign and discovered great property for traffic sign identification. In [8], the Driver Advocate is referred as an adaptive driver support technique that merges several AI approaches particularly, brokers, ontology, creation frameworks, and machine learning strategies are dealt. Fleyah and Devami presented a framework depends on conjuring the principal component analysis (PCA) technique for selecting the best part of traffic sign images for classifying anonymous road signs [9].

Andrzej et al [10] have utilized conventional three-phase system including detection, recognition and tracking phases. The equiangular polygons instances are captured by the detector which are separated for extracting the shading information and set up the regions of interests. The location and the size of the identified sign nominee are predicted by the tracker. The classifier is employed to compare the discrete color of the detected sign with the sample images regarding to the class-specific sets of discriminative neighborhood regions.

Elaborated study of the traffic sign recognition literature, enumerating discovery frameworks for traffic sign recognition (TSR) to assist drivers is provided in [7]. They portrayed the contributions of latest attempts to the different phases inherent in traffic sign recognition: segmentation, feature extraction, and detection of traffic signs. In other hand, the well-known Viola-Jones detector has employed shape-based techniques utilized either Haar-like features in systems and the Generalized Hough Transform is needed for the intensity and the direction of image gradients in systems. The works of Bahlmann et al. [11] and by Brkic et al. [12] is used at the initial sub-division of the work, whereas the Regular Polygon Detector [13], the Radial Symmetry Detector [14], the Vertex Bisector Transform [15], the Bilateral Chinese Transform are found at the second sub-division. Likewise, Houben [16] has presented two techniques of Single Target Voting (STV) for circular and triangular shapes.

Numerous latest methodologies utilize gradient orientation data in the discovery stage, for instance, Edge Orientation Histograms are calculated over shape-specific sub-regions of the image [11]. Gao et al. [17] have proposed a novel technique that compares the local edge orientations for classifying the candidate traffic signs at arbitrary obsession points along with those of the templates. The color-based segmentation is used to obtain the Regions of Interest (ROI) which is then classified utilizing the HOG feature [18]. Creusen et al. [19] link the HOG descriptors computed on every one of the color channels in order to coordinate color information at the HOG descriptor. Some of the advantages of such feature are the local contrast normalization, the coarse spatial sampling, scale-invariance, and the fine weighted orientation binning.

3. Proposed Methodology

The work flow of the proposed traffic sign detection system is given in Figure 1. It comprises of five different phases such as,

- Preprocessing
- Segmentation
- Detection
- Feature extraction
- Classification

3.1. Preprocessing

Initially the input images were considered as raw images which are not applicable for traffic sign detection, in which unwanted and redundant pixels were removed on preprocessing. Next the noises in the images were reduced by applying median filtering technique. During this stage it conserves all essential details in an image. In this process all individual pixels with its neighboring pixels were compared using median filtering. The original pixel value is replaced by median values of neighboring pixels. It replaces the entire mid pixel value by sorting the pixel values. Figure 3 shows the preprocessing result of given sample traffic sign images.

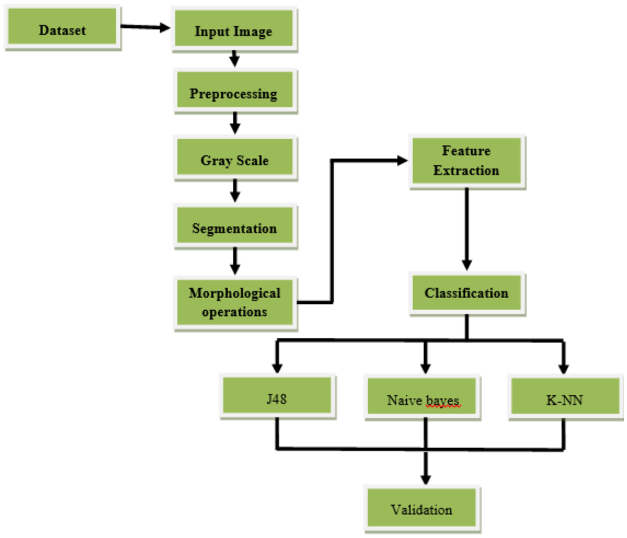

Fig. 1. Flow diagram of proposed technique.

(a) (b)

Fig. 2. (a) Original Image, (b) Gray level

(c) (d)

Fig. 3. (c) Original Image, (d) Segmentation.

3.2. Segmentation

In medical image processing, segmentation is the process of extracting the traffic sign region from the normal region. Through the following steps the segmentation of traffic sign region is accomplished. At first, binary conversion is done for the preprocessed traffic sign images with threshold cut-off of 128. The pixel values below than the given threshold are mapped to black whereas the remaining higher value pixels are mapped to white. Because of this, several regions are established throughout the traffic sign which are then cropped out. Then the white pixels are eliminated by applying morphological erosion operation at the second step. The actual traffic sign image and the eroded region are split into two equal regions and the extracted black pixel region is denoted as a mask of traffic sign image. In this article, Berkeley wavelet transformation is applied to obtain effective traffic sign segmentation of camera image.

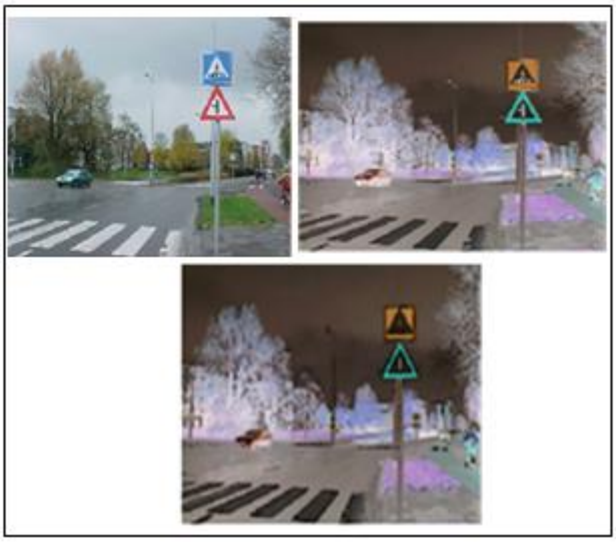

Figure 4: (e) Original Image (f) Inverted Image (g) Eroded Image

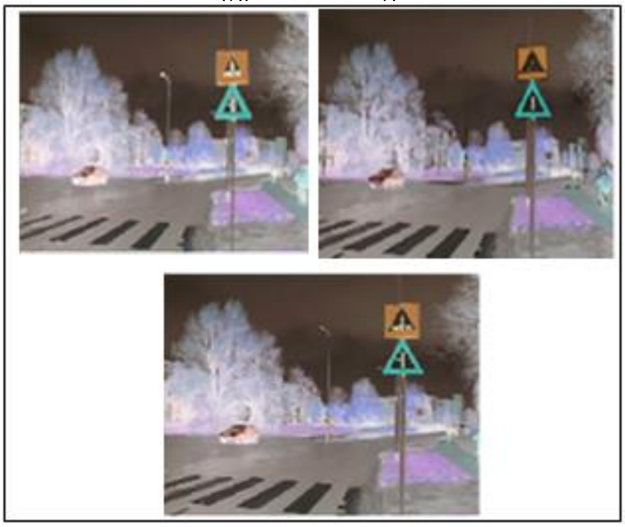

Fig.5. (h) Dilated image, (i) Opened image, (j) Closed image

3.4. Traffic sign detection

In our proposed system, the traffic signs are detected based on the color and shapes of the traffic signs.

Fig.6. (k) Original image (l) Detected Traffic Signs

Three different colors like red, blue, and green are taken and the common three different shapes such as circular, square, and triangular shapes are considered. The proposed detection is done by heuristics functions and the detected traffic signs are given in Figure 6.

3.4. Feature Extraction

3.4.1 Texture Based Features

Texture based features are known as higher-level image information such as Mean, Variance, Standard deviation, Entropy, Kurtosis, Skewness, Contrast, Correlation, Energy and Homogeneity. For machine learning and of human visual perception the texture analysis is considered as an essential parameter. It is required to enhance the precision of diagnosis system by choosing essential features.

Table 1

Extracted texture based features

S.No	Mean	Std	Entropy	RMS	Variance	Kurtosis
Image 1	87.265	57.48	7.3399	14.9308	2.94E+03	1.7941
Image 2	156.919	40.8557	6.7814	5.9673	.49E+03	3.8804
Image 3	124.5572	63.0523	7.5874	15.9668	3.09E+03	2.3508
Image 4	96.1901	68.0926	7.4945	15.9233	3.37E+03	2.7137
Image 5	113.8322	65.7903	7.3183	15.3031	3.88E+03	2.6473

S.No	Skewness	Contrast	Correlation	Energy	Homogeneity
Image 1	0.1383	0.1481	0.9758	0.1408	0.9422
Image 2	-1.034	0.2494	0.9287	0.184	0.927
Image 3	0.6125	0.4127	0.9474	0.1114	0.8754
Image 4	0.9436	0.4934	0.9486	0.1039	0.8631
Image 5	0.149	0.5557	0.9289	0.126	0.8719

3.5. Classification

3.5.1. Naïve Bayes

Naive Bayes Classifiers are one of the classifiers which made assumption on the features that are statistically independent of each other. Other classifiers assume that there will be few correlations among features for a given class but the features of naïve bayes classifier are conditionally independent for a given class. While this may appear an excessively oversimplified (naive) confinement on the information, practically the naïve bayes is aggressive with more advanced strategies and appreciates some theoretical assist for its viability. Due to the assumption of independence, the naïve bayes are extremely scalable and independence, the naïve bayes are extremely scalable and has the ability to quickly learn the usage of high dimensional features with limited training data. It is useful on datasets of several real world applications where the volume of data is small compared to the number of features for every single segment of data like image, text and voice data. Medical image processing, Spam filtering and vocal emotion recognition are some of the examples of advanced applications.

3.5.2. Decision Tree (J48)

J48 is one of the types of decision tree classification algorithm. It is a classification framework which is based on the machine learning techniques that performs classification based on the attributes of the accessible data for an instance. C4.5 is another type of decision tree algorithm for developing univariate trees. Its operation depends on the fact that when developing the tree in a recursive manner, it puts that attribute at the origin that possesses the maximum data gain. C4.5 is an implementation of WEKA of J48 algorithm which we employed to perform classification. In order to detect Alzheimer's disease with various modalities, the C4.5 algorithm has just been utilized.

3.5.3. K-Nearest-Neighbor (KNN) Classification

K-nearest neighbor (KNN) is a kind of classification algorithm to classify objects as per the nearest training instances at the feature space. It is the simplest classification algorithm of all the machine learning techniques. The process of training for such algorithm just comprises of storing feature labels and feature vectors of the training images. The unlabelled query points are just allocated to the label of their k-nearest neighbors in the process of classification. Generally, the classification of objects depends on the labels of their nearest neighbors through dominant vote. If the k value is equal to 1, then the object is just classified as the object class closest to it and the if the k value is an odd integer, then it is obtained that there are just two classes are present. Nevertheless, there can be ties while executing multiclass classification when the k value is an odd integer. In order to transform every image to a fixed length vector with real numbers, the most general distance function is applied for k-nearest neighbor that is the Euclidean distance:

$$d(a,b) = \| a-b \| = \sqrt{(a-b).(a-b)}$$

$$= \left(\sum_{j=1}^{n} \left((a_j - b_j)^2 \right) \right)^{1/2} \qquad (1)$$

Where, a and b are histograms in $H = R^m$

4. Experimental results

The experiment is performed with 50 traffic images captured by camera at various places on the road and which we collected from internet. These images are applied to number of image processing techniques such as preprocessing, segmentation, morphological operation, traffic sign detection, feature extraction, and classification. The obtained results are shown in the above corresponding sections. The texture based features are derived which is ten formed into a dataset and the classification is performed in WEKA tool. There are three classifications such as Naïve Bayes, decision tree (J48), and k-nearest neighbor (knn) are applied on the derived dataset and their results are demonstrated in Table 2, Table 3, and Table 4.

Table 2
Classification Results of J48

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area
0.778	0.833	0.737	0.778	0.757	-0.059	0.551
0.167	0.222	0.200	0.167	0.182	-0.059	0.551
0.625	0.681	0.603	0.625	0.613	-0.059	0.551

Table 3
Classification Results of KNN

TP Rate	FP Rate	Precisi on	Recal l	F-Measure	MCC	ROC Area
0.778	0.667	0.778	0.778	0.778	0.111	0.500
0.333	0.222	0.333	0.333	0.333	0.111	0.718
0.667	0.556	0.667	0.667	0.667	0.111	0.554

Table 4
Classification Results of Naïve Bayes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area
0.500	0.333	0.818	0.500	0.621	0.145	0.556
0.667	0.500	0.308	0.667	0.421	0.145	0.537
0.542	0.375	0.691	0.542	0.571	0.145	0.551

4.1. Comparative Analysis

The result obtained using the proposed traffic sign detection technique based on morphological segmentation with kNN classifier is compared with the J48 and Naïve Bayes classifier on the basis of performance measure such as sensitivity, specificity, and accuracy. The detailed analysis of performance measures is shown in Table 5 and, through the performance measure, it is depicted that the performance of the proposed methodology of kNN classifier has significantly improved the traffic sign detection compared with the J48 and Naïve Bayes based classification techniques. The obtained classifier outputs are plotted for comparison which is demonstrated in Figure 7.

4.2. Comparative parameters

A. Accuracy

Accuracy is defined as the ratio of number of right assessment to the number of total assessments. From the whole dataset the number of suitable images were extracted initially then compared with the whole dataset by using the following formula where errors and quality of data were the significant factors that are measured in terms of percentage (%).

$$Accuracy = ((TN+TP))/((TN+TP+FN+FP)) \quad (2)$$

Where, TN-True Negative, TP-True Positive, FP-False positive and FN-False Negative.

B. Sensitivity

To measure sensitivity, the number of true positive and false negative are extracted and added. The sensitivity is defined as the ratio of the number of true positive to the added measure of true positive and false negative. The accurately recognized data mention the level of positive values. It is measured by applying the following formula and it is measured in terms of percentage (%).

$$Sensitivity=TP/ ((TP+FN)) \quad (3)$$

C. Specificity

Specificity is used to predict the effect of changes at the output due to its changes at the input datasets. It is measured from the correctly recognized negative values and the specificity is measured by percentage (%). It is defined as the ratio of the number of negative assessments to the sum of number of true negative and false positive assessments. The following formula represents the specificity.

$$Specificity = TN/ ((TN+FP)) \quad (4)$$

Table 5
Comparison of classifier outputs

Evaluation parameter	KNN	J48	Naïve Bayes
Specificity (%)	0.777	0.699	0.541
Sensitivity (%)	0.333	0.166	0.266
Accuracy (%)	0.666	0.625	0.514

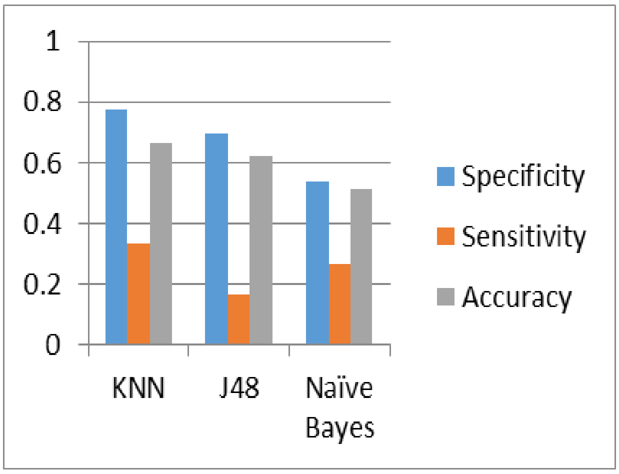

Fig. 7. Comparison of classifier outputs.

5. Conclusion

In this paper, we have investigated traffic sign detection for camera images taken on the highways. Several images are applied to perform the experiment and from that it is clearly observed that the proposed technique can able to detect the traffic signs fast and precise when compared to the manual detection of drivers. Improved performance of different performance factors such as accuracy, sensitivity and specificity shows that our proposed technique provides better results. The experimental results demonstrate that the proposed technique can help in the precise and timely traffic sign detection on camera images with perfect discovery of its correct location. Hence, the proposed technique is crucial for traffic sign detection on camera images. The effectiveness of the proposed technique is measured from detection accuracy which is 96% obtained from experimental results. The obtained results prompt the conclusion that our proposed technique is appropriate to accurately discover the traffic sign on the highways.

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