Real Time Road Sign Recognition System For Autonomous Car

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Abstract— **The car is essential part of our life and it is ready to change from luxury to convenience. An Artificial Intelligent Driver Assistance System will help vehicle drivers to react to changing road signs, road lanes, traffic panel and other road conditions which can potentially improve driver safety. The goal of this paper is to present a brief survey of road sign recognition system for autonomous cars. In addition to this, the paper also highlights various standard available road sign database. Road sign recognition sys tem is divided in three steps: road sign detection, road sign tracking and road sign classification or recognition. The paper presents a comparative survey of existing methods of road sign detection, road sign tracking and road sign classification. In proposed method for detection of road sign from live video frames ORB (Oriented FAST and rotated BRIEF feature) detector is used. Detected road sign is match with the all Indian Road Sign database. Matching process is done by Brute Force matches which match the key point and descriptor of detected sign and database sign. After evaluating all matched parameter sign recognition is performed.**

***Keywords*— Indian standard road sign database, road sign detection, matching, recognition., ORB detector, BF matcher.**

I. Introduction

An autonomous car is able to sense its environment and navigate without human input. Autonomous cars combine a variety of techniques to perceive their surroundings, including radar, laser light, GPS, odometry and computer vision. In August 1961, Popular Science reported on the Aero mobile 35B, an air-cushion vehicle (ACV) that was invented by William Bertelsen and was envisioned to revolutionize the transportation system, with personal self-driving hovering cars that could speed up to 1,500MPH. A decade after Elon Musk announced Tesla's first master plan; he has just come up with its sequel-a grand outline that has been called out for being "absurd," and "insane," while simultaneously "brilliant" and "magnificent" Tesla model S, X, 3 is currently offering Autopilot, an advanced driver assist mode that can self-steer, brake, and switch lanes. An Intelligent Driver Assistance System will help vehicle drivers to react to changing road sign, road lane, traffic panel and other road conditions which can potentially improve driver safety [7].

The changes in weather conditions or viewing angles, traffic signs and panels increase difficulty to recognize road sign. Hence, development of such an automatic system inside cars will certainly improve driving safety to a great extent. Some of the lead automobile industries are working for the development of their own driverless car. The levels of self-driven vehicle autonomy are mentioned in Table 1

TABLE I
5 Level of self –driven Vehicle Autonomy

Specification	**Level 0**	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
	No Automation	Driver Assistance	Partial Automation	Conditional Automation	High Automation	Full Automation
Execution of steering and Acceleration/ De-acceleration	Human Driver	Human Driver	System	System	System	System
Monitoring of driving environment	Human driver	Human driver	System	System	System	System
Fullback performance of dynamic driving task	Human driver	Human driver	Human driver	Human driver	System	System
System capability	N/A	Some driving mode like adaptive cruise control	Some driving modes like Antilock braking system, speed control	Some driving modes like Active break assist, blind spot assist, active lane change assist,	Some driving modes like active emergency stop assist, active parking	All driving modes

				cross driving function	assist, active steering assist, remote parking summon	
Mode	All most available commercial AI cars	Mercedes-Benz, BMW, Tesla, Audi, Volkswagen, GM, Cadillac	Mercedes-Benz, Tesla, Ford	Google-wayMo, Ford, BMW, Peugeot- Citroën	GM, Mercedes-Benz, BMW, Aptiv, Volvo, Tesla	Volkswagen Group, BMW, Renault-Nissan-Mitsubishi Alliance, Volvo, Tesla
1. Official	All	Cadillac super cruise,	Peugeot 3008	wayMo Chrysler Pacifica	Mercedes-Benz F015, Tesla model S, X, and 3	BMW iNEXT, Volvo 360s
2. Commercial	All	Cadillac Escalade, BMW Genius, BMW M-series	Peugeot 3008, BMW X-series	Audi A8, Tesla Model 3	Active self-driving concept in BMW 540i, Nissan taxi, Tesla modelS,X and 3	N/A
3. Conceptual	All	-	-	Audi A8 E-tron	GM CRUISE AV, Mercedes-Benz F015	Sedric, BMW iNEXT, Volvo 360s

The features of level 4 and level 5 cars are mentioned below.
1. Automatic Road sign and road panel recognition system-ARSR
2. Auto steer
3. Blind Spot Detection
4. Side Collision Warning
5. Summon
6. Auto park (Automatic human, car and object detection)
7. Automatic Emergency Braking and Steering
8. Automatic High Beams
9. Auto Lane Change (Automatic road lane recognition system)
10. Speed Assist.

Automatic parking system with human detection system and speed road sign recognition system are available in 4th Level Volvo XC60 which is shown in Fig.1.

(a) (b)

Fig.1. (a) Automatic Road sign recognition system in Volvo XC60 (b) Automatic parking system in with human detection in Volvo XC60

This paper presents a brief review of vision-based road sign recognition system that can be incorporated in level 4 and level 5 autonomous cars. Road sign recognition is one of the critical parts of autonomous navigation system. To capture the attention of driver not all sign is equal in their ability. The purpose of the paper and survey on road sign recognition is to get road sign database provided by government to recognize road sign as there is a huge scope of work left behind to build standard road sign database worldwide. This paper provides critical review of road sign database, road sign detection, tracking and classification methods in section 2, section 3 provides proposed detection method and matching method for real time road sign recognition and section 4 concludes the details presented in this paper.

II. LITERATURE SURVEY

Detection and recognition of road sign in a complete scene is necessary as not all signs are equal in their ability to capture the attention of the driver. For example, a driver may fixate his gaze on a sign but neither notices the sign nor remembers its informational content. Fig. 2 shows examples on how ARSR can be used for driver assistance. Instead of focusing on detection, perfectly recognizing all signs of some class would be the objective for an autonomous car.

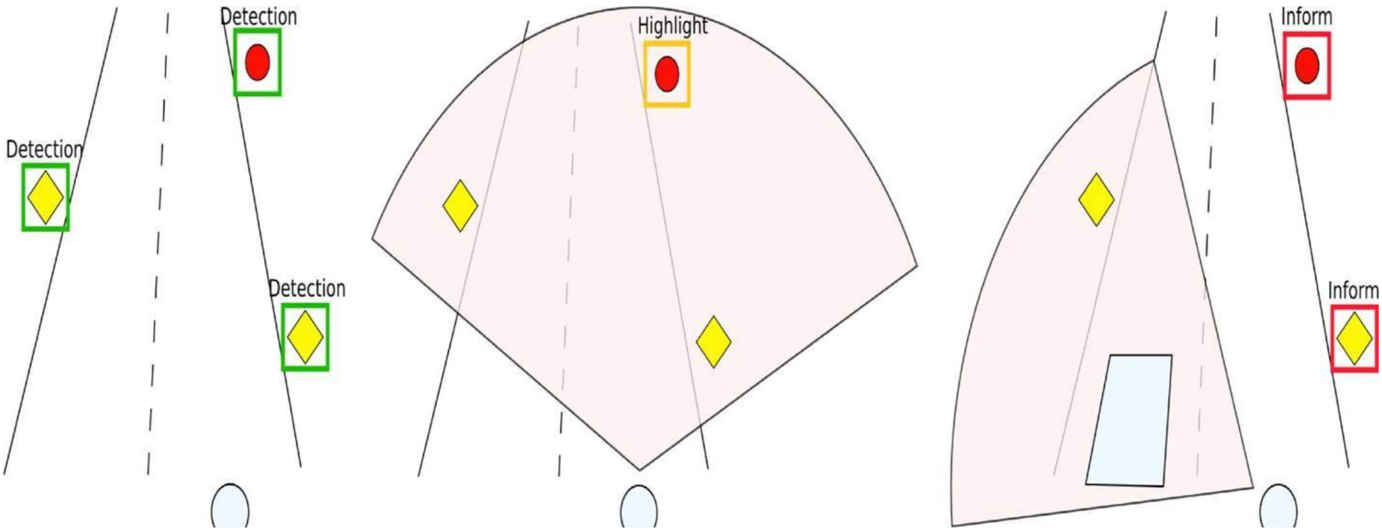


Fig.2. (a) Standard scenario used for autonomous cars. Here, all signs must be detected and processed. In (b), the driver is attentive and spots all signs. Therefore, the system just highlights the sign that is known to be difficult for people to notice. In (c), the driver is distracted by a passing car and thus misses two signs. In this case, the system should inform the driver about the two missed signs [1].

A. Survey of road sign Database

Road sign recognition database is an essential part of the autonomous system. In 1968, the Europe countries signed an international treaty, called the Vienna convention on road traffic, for the basic traffic rules. A part of this treaty defined the traffic signs and signals [3]. As a result, in Europe the traffic signs are well standardized, although not all countries are participants of these rules and local variations in practice may be found. In spite of appearances of traffic signs being strictly pre-scribed by the Vienna convention, there still exist variations between countries that have signed the treaty [13]. Road signs in the Republic of India are similar to those used in some parts of the United Kingdom. Most urban roads and state highways have signs in the state language and English. In 2012, the Tourism department of Kerala announced plans to upgrade road signs in the state to include maps of nearby hospitals. The Noida Authority announced plans to replace older signboards with new fluorescent signage. Indian Roads Congress (IRC) provide legal database on a non-commercial basis. In the U.S., traffic signs are regulated by the Manual on Uniform Traffic Control Devices (MUTCD) [12]. It defines which signs exist and how they should be used. It is accompanied by the Standard Highway Signs and Markings (SHSM) book, which describes the exact designs and measurements of signs. New Zealand uses a sign standard with warning signs that are yellow diamonds, as in the U.S., but regulatory signs are round with a red border, like those from the Vienna Convention countries [1] Japan uses signs that are generally in compliance with the Vienna Convention, as are Chinese regulatory signs. Chinese warning signs are triangular with a black/yellow colour scheme. Central and South American countries do not participate in any international standard but often use signs somewhat like the American standard. Fig.3. gives the different road signs, indicating pedestrian in various countries. New Zealand uses a sign standard with warning signs that are yellow diamonds, as in the U.S., but regulatory signs are round with a red border, like those from the Vienna Convention countries.

(a) China (b) USA (c) India (d) Sweden

(e) Japan (f) Germany (g) Russia (h) Australia

(i) Spain (j) Czech republic (k) Singapore (l) Korea

Fig.3. different road signs, indicating pedestrian sign in various countries.

Japan uses signs that are generally in compliance with the Vienna Convention as are Chinese regulatory signs. Chinese warning signs are triangular with a black/yellow colour scheme. Central and South American countries do not participate in any international standard but often use signs somewhat like the American standard. While signs are well defined through laws and designed to be easy to spot, there are still plenty of challenges for TSR systems [1]. Table.2 shows Available standard and public road sign database by various country.

TABLE II
Available Road Sign Database

Reference	**Database**	**Remark**
https://mutcd.fhwa.dot.gov/ser-shs_millennium.htm	Standard Highway Signs and Markings (SHSM) [1] in USA	Standard
http://benchmark.ini.rub.de/	German TSR Benchmark (GTSRB) [1]	Public database
https://mutcd.fhwa.dot.gov/	Manual on Uniform Traffic Control Devices (MUTCD) [3] in USA	Public database
https://data.qld.gov.au/dataset	Department of transport and main road, Queensland, Australia	Public database
–	Central and South American countries do not participate in any international standard but often use signs somewhat like the American standard [1]	Standard
https://keralapolice.gov.in	Tourism department of Kerala (Indian database)	Standard

https://data.gov.in/sector/transport	Tamil Nadu State Transport Corporation (TNSTC), India and Open Data initiative of Government of India Traffic control road sign database	Standard
http://www.irc.nic.in/	Indian Roads Congress (IRC) provide legal database	Standard

B. Survey of road sign Detection Methods

To extract road sign from image, complete scenes are necessary. In addition to this, many detection systems rely on a tracking scheme to make detection more robust. Andreas Møgelmose et. al. [1] introduced two kinds of detection methods: colour-based method and shape-based method. In colour-based method they extract colour from input image and use as base for detection. In shape-based method they ignore colour in favour of characteristic shape of sign. HOG is first proposed for human detection and becomes a widely used for shape descriptor in human detection [2].in order to extract HOG with colour information, which is very important for traffic sign detection as N. Dalal explain, the original HOG calculate gradients for each colour channel and takes the gradient with largest norm [7].

Yi yang et al. [2] proposed to compute HOG feature on probability map as to make full use of colour and shape information of traffic sign. In paper [3] they detect text traffic sign candidates using MSER (Maximally stable extreme region) and HSV colour thresholding. Other methods for traffic sign detection that are carrying out edge detection and shape recognition over grey-scale images have been developed. A robust-shaped detector like the Álvaro González says Hough transform is typically used because it is very robust to changing illumination and occlusions. However, this transform is slow to compute over large images, and it has to work with a wide range of variation in the appearance of the traffic signs and panel over the images [4]. They also describe the Visualise system is based on the light retro reflection principle. It uses an active infrared illuminator whose features are perfectly defined and known apriori as a pattern light source. The part of infrared light that comes into contact with the signs and panels is reflected. The reflected light is captured by a stereoscopic system made up of two high-resolution came. Different algorithms have been proposed to reduce the computational time of the Hough transform; a multidimensional quad tree structure for accumulating is suggested in [14] a method based on the fact that a single parameter space point can be determined uniquely with a pair, triple, or generally n-tuple of points from the original picture. For Road sign extraction Yi Yang, Hengliang Luo describe traffic signs are detected by finding maximally stable extremal regions from grey image for traffic signs with white background and from normalized red/blue image for traffic signs with red or blue background [2]. They extract maximally stable extremely regions from probability maps instead of Grey image or normalized red/blue image. This is because our probability maps increase the contrast between traffic signs and background, which could result in more accurate and easier extraction.

Alvaro Gonzalez in [2] suggest VISUAL Inspection of Signs and panels ("VISUALISE"), which is an automatic inspection system, mounted onboard a vehicle, which performs inspection tasks at conventional driving speeds. VISUALISE allows for an improvement in the awareness of the road signalling state, supporting planning and decision making on the administration's and infrastructure operators' side. They used stereo correlation method for detection and segmentation of road sign. Table 3 shows the methods of road sign detection, road sign feature and segmentation.

TABLE III
Comparison table of road sign Detection Method

Paper no	**Year**	**Segmentation method**	**Feature**	**Detection method**	**Remark**
[18]	2018	Probabilistic colour pre-processing	HOG feature	Multiclass SVM classifier	Apply logic boost
[17]	2017	Morphological Operation	Edges	SVM	-
[13]	2016	HSV thresholding	Triangle, Rectangle, octagon	Template Matching	
[3]	2015	Large intra class variation	Dense feature	Dense feature extractor	-
[1]	2015	HSV colour thresholding	Text information	Maximally stable external region method (MSER)	-

[10]	2014	Adaptive thresholding and colour segmentation	Oriented Fast and Rotated BRIEF (fast corners)	SVM	-
[2]	2012	HSI thresholding	Edges	Cascade classifier	Linear SVM also can be used
[3]	2014	HSV colour thresholding	Sign shape	Blob detection	5 stage cascade classifiers with logic boost
[17]	2011	Stereo correlation	Triangle, Rectangle and arrow	Hough transform and canny edge detection	Euclidian nearest neighbours

C. Survey of Road Sign Tracking Method

Once a candidate sign is detected, it is unnecessary to search for it in the consecutive frames in every possible location. In paper [2], [3],[5],[7] authors have not used a tracking system but had directly use recognition system. In [10] authors use tracking to track road sign in incoming live video frame. Basic road sign tracker is composed of three complementary parts. Complementary parts of Kalman filter are given in below equations.

$$X(n)A(n)*X(n-1)+U(n) \tag{1}$$

$$Z(n)=H(n)X(n)+V(n) \tag{2}$$

Where, X(n), U(n) and A represent state vector, zero mean vector at time of n, and a state transition matrix, Respectively. further, Z(n), H(n) and V(n) represent an observation vector whose element are observed values, and observation matrix, and zero mean observation noise vector at time of n respectively. Then, the Kalman filter algorithm is representing as follows:

$$Pb(n) = M(n)*P_a(n-1)M^T(n) + Q_U(n), \tag{3}$$

$$K(n) = P_b(n)H^T(n)\ H(n)P_b(n)H^T(n) + Q_V(n) -1, \tag{4}$$

$$\bar{X}(n) = M(n)\hat{X}(n-1), \tag{5}$$

$$\hat{X}(n) = \bar{X}(n) + K(n)\ Z(n) - H(n)\bar{X}(n), \tag{6}$$

$$P_a(n) = P_b(n) - K(n)H(n)P_b(n). \tag{7}$$

Where, K(n) is called a Kalman gain matrix. Further, QU(n) and QV(n) are covariance matrices of U(n) and V(n), respectively. The vectors $\bar{X}(n)$ and $\hat{X}(n)$ denote the estimation results of X(n) at the times of n − 1 and n, respectively. By using the Kalman filter, the state vector X(n) is estimated from $\hat{X}(n-1)$, and $\bar{X}(n)$ is obtained. Further, $\bar{X}(n)$ is compensated by the Kalman gain K(n) and the noisy observation vector Z(n) at the time of n to obtain the final estimation result $\hat{X}(n)$. Consequently, the Kalman filter can accurately estimate the state by iterating the state transitions.

Tomoki Hiramatsu et al. [7] proposed a new approach for adaptive restoration of in-vehicle camera foggy images using Kalman filter. He gave state transition model on new restoration method. Alvaro Gonzalez [7] suggested that proposed detection system is sensitive to some particular image size and Kalman filter is used to track a sign through the frames until it is sufficiently large to be recognized as a specific standard sign. Road sign tracking comparison discussed in Table.4

TABLE IV

Comparison Table of Road Sign Tracking

Paper no	Year	Sign type	Rea time impleme nt	Model vs Training	Tracking
[18]	2018	Edges	YES	Both	Kalman filter
[17]	2017	Circle, Triangle	YES	Both	Liner kalman filter
[13]	2016	Triangle, Rectangle, Octagon	YES	Both	Not used
[1]	2015	Circular road sign	N/A	Training	Mentioned but not implement
[10]	2015	Octagon, circle, tringle, square, rectangle, arrow panel, another object	N/A	Training	Not used

[2]	2014	Square panels	YES	Both	Tracking using Kalman filtering
[3]	2014	Square and rectangle	YES	Both	Not used
[17]	2012	Triangle, Circle	YES	Both	Not used
	2011	Octagon, circle, tringle, square, rectangle, arrow panel	YES	Both	Kalman filtering used for tracking

D. Survey of Road Sign Recognition Method

In detection step, detected road sign classified into their super class. However, we still do not know which subclass they belong to. There are many false positives in detected sign. Therefore, we have to further classify the detection sign into their sub-class or background. Yi yang train three CNNs for classify road sign in super class [2]. All three CNNs share the same structure.

Each CNN contains two convolution layers and two sub sampling layers, pulse a full- connected MLP in the last two layers. the size of filter kernel in both of two convolution layers is 5x5 and L2-pooling is used in sub sampling layers. The size of input image is 32x32, after the first convolution layer, there are 16 feature maps with size of 28x28. then the next sub sampling layer resizes the feature maps to 14x14.aftert the second sub sampling layer, 32 feature maps with the size of 5x5 are obtained. then theses feature maps are reshaped to a long vector with length 800[2]. Jack Greenhalgh suggested how to increase the chances of OCR in recognizing Noisy text region from detected road sign [3]. They apply an approximate perspective transform to rectangular candidate region in order to vertically align them and their text characters. Individual text characters are then segmented, formed into words, and then sent to OCR. Result from several instances of each traffic sign are then combined [3].

Alvaro [7] analysed the system and able to detect up to 99% of the sign and panels present on road in Spain. This method is able to detect 500 road signs. Manual measurements are taken using calibrated retro reflectivity equipment that uses a narrow light beam emitter. This implies that manual measurements need to be taken, in particular, selected points of the sign or panel under inspection. In Table.5 Recognition of road sign and various classifications method is described. Fig.4. shows GTSDB data based sign classified in different sub classes. Second row shows Danger road sign. Third row shows mandatory road sign [2].

TABLE V

Comparison table of Road sign classification and Recognition

Paper no	Year	Classification method	Accuracy	Used Database
[18]	2018	Convolutional Neural Network (CNN)	98.24%	-
[17]	2017	SVM Classifier	92.45%	-
[13]	2016	Pixel Matching	83.33%	Bangali Road Sign Database
[3]	2015	Object class with large inra-class variance	50% overall Accuracy	KITTI , GTSDB
[1]	2015	Convolutional Neural Network (CNN)	Overall classification Accuracy is 98.24% to 98.77%	GTSDB GTSRB, CTSD
[10]	2014	Histogram of OCR	93% accurate detection and 89% accurate recognition	UK text based traffic sign database
[2]	2014	Only tracking done	-	-
[3]	2012	Cascade classifier	Able to do segmentation, feature extraction and detection but not used tracking for accurate system	KUL dataset, GTSRB dataset
[17]	2011	Classification based on luminance and shape of signs	99.52% detection accuracy, 91.66% of reliability	Not mentioned

Fig .4 The examples of sub-classes of GTSDB. First row shows Prohibitory road sign.

III. Proposed Work

A. Road sign Detection:

Proposed method is well known FAST **Features** from accelerated segment test key point detector and recently developed BRIEF-binary robust independent elementary feature descriptor. For this reason, new method is known as ORB (Oriented FAST and Rotated BRIEF). **Oriented FAST and rotated BRIEF (ORB)** is a fast-robust local feature detector, first presented by Ethan Rublee et al. in 2011; both these techniques are attractive because of their good performance and low cost.

ORB is basically a fusion of FAST key point detector and BRIEF descriptor with many modifications to enhance the performance. First it uses FAST to find key points, then apply Harris corner measure to find top N points among them. It uses pyramid to produce multiscale-features. But one problem is that, FAST doesn't compute the orientation. Now, what about rotation invariance? Authors came up with following modification. It computes the intensity weighted centroid of the patch with located corner at center. The direction of the vector from this corner point to centroid gives the orientation. To improve the rotation invariance, moments are computed with x and y which should be in a circular region of radius r, where r is the size of the patch. Now for descriptors, ORB use BRIEF descriptors. But we have already seen that BRIEF performs poorly with rotation. ORB does is to "steer" BRIEF according to the orientation of key points. For any feature set of n binary tests at location (x_i, y_i), define a $2 \times n$ matrix, S which contains the coordinates of these pixels. Then using the orientation of patch, θ, its rotation matrix is found and rotates the S to get steered(rotated) version.

ORB discretize the angle to increments of $2\pi/30$ (12 degrees), and construct a lookup table of precomputed BRIEF patterns. As long as the key point orientation θ is consistent across views, the correct set of points S_θ will be used to compute its descriptor. BRIEF has an important property that each bit feature has a large variance and a mean near 0.5. But once it is oriented along key point direction, it loses this property and become more distributed. High variance makes a feature more discriminative, since it responds differentially to inputs. Another desirable property is to have the tests uncorrelated, since then each test will contribute to the result. To resolve all these, ORB runs a greedy search among all possible binary tests to find the ones that have both high variance and means close to 0.5, as well as being uncorrelated. The result is called **BRIEF**.

B. Road Sign Matching:

Brute-Force matcher is simple. It takes the descriptor of one feature in first set and is matched with all other features in second set using some distance calculation. And the closest one is returned. In order to apply brute-force search to a specific class of problems, one must implement four procedures, *first*, *next*, *valid*, and *output*. These procedures should take as a parameter the data *P* for the particular instance of the problem that is to be solved, and should do the following:

1. *first* (*P*): generate a first candidate solution for *P*.
2. *next* (*P*, *c*): generate the next candidate for *P* after the current one *c*.
3. *valid* (*P*, *c*): check whether candidate *c* is a solution for *P*.
4. *output* (*P*, *c*): use the solution *c* of *P* as appropriate to the application.

The *next* procedure must also tell when there are no more candidates for the instance *P*, after the current one *c*. A convenient way to do that is to return a "null candidate", some conventional data value Λ that is distinct from any real candidate. Likewise, the *first* procedure should return Λ if there are no candidates at all for the instance P. The brute-force method is then expressed by the algorithm

$c \leftarrow first(P)$
while $c \neq \Lambda$ **do**
 if $valid(P,c)$ **then** $output(P, c)$
 $c \leftarrow next(P,c)$
end while

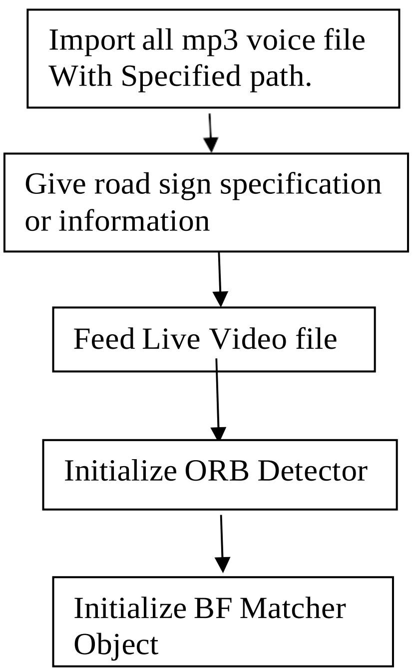
BF matcher is inbuilt in Open cv image processing library For BF matcher, first we have to create the BFMatcher object using **cv2.BFMatcher()**. It takes two optional params. First one is norm Type. It specifies the distance measurement to be used. By default, it is cv2.NORM_L2. It is good for SIFT, SURF etc (cv2.NORM_L1 is also there). For binary string-based descriptors like ORB, BRIEF, BRISK etc, cv2.NORM_HAMMING should be used, which used Hamming distance as measurement. If ORB is using WTA_K == 3 or 4, cv2.NORM_HAMMING2 should be used.

Second param is Boolean variable, crosscheck which is false by default. If it is true, Matcher returns only those matches with value (i,j) such that i-th descriptor in set A has j-th descriptor in set B as the best match and vice-versa. That is, the two features in both sets should match each other. It provides consistent result, and is a good alternative to ratio test proposed by D.Lowe in SIFT paper. Once it is created, two important methods are *BFMatcher.match()* and *BFMatcher.knnMatch()*. First one returns the best match. Second method returns *k* best matches where k is specified by the user. It may be useful when we need to do additional work on that.

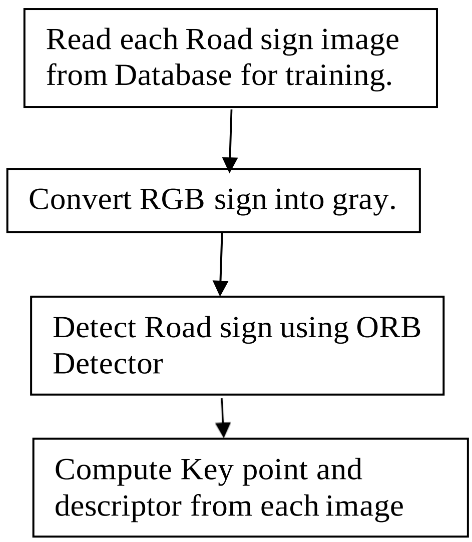
Like we used cv2.drawKeypoints() to draw key points, **cv2.drawMatches()** helps us to draw the matches. It stacks two images horizontally and draw lines from first image to second image showing best matches. There is also **cv2.drawMatchesKnn** which draws all the k best matches. If k=2, it will draw two match-lines for each key point. So, we have to pass a mask if we want to selectively draw it. Below Algorithm shows BF matching method with ORB descriptor and key points.

Proposed system algorithm is divided into 3 phases:
Phase 1: Initialize Detector and BF matcher
Phase 2: Detect road sign from Train Image
Phase 3: Detect road sign from query image and match with train image and recognise which sign it is.

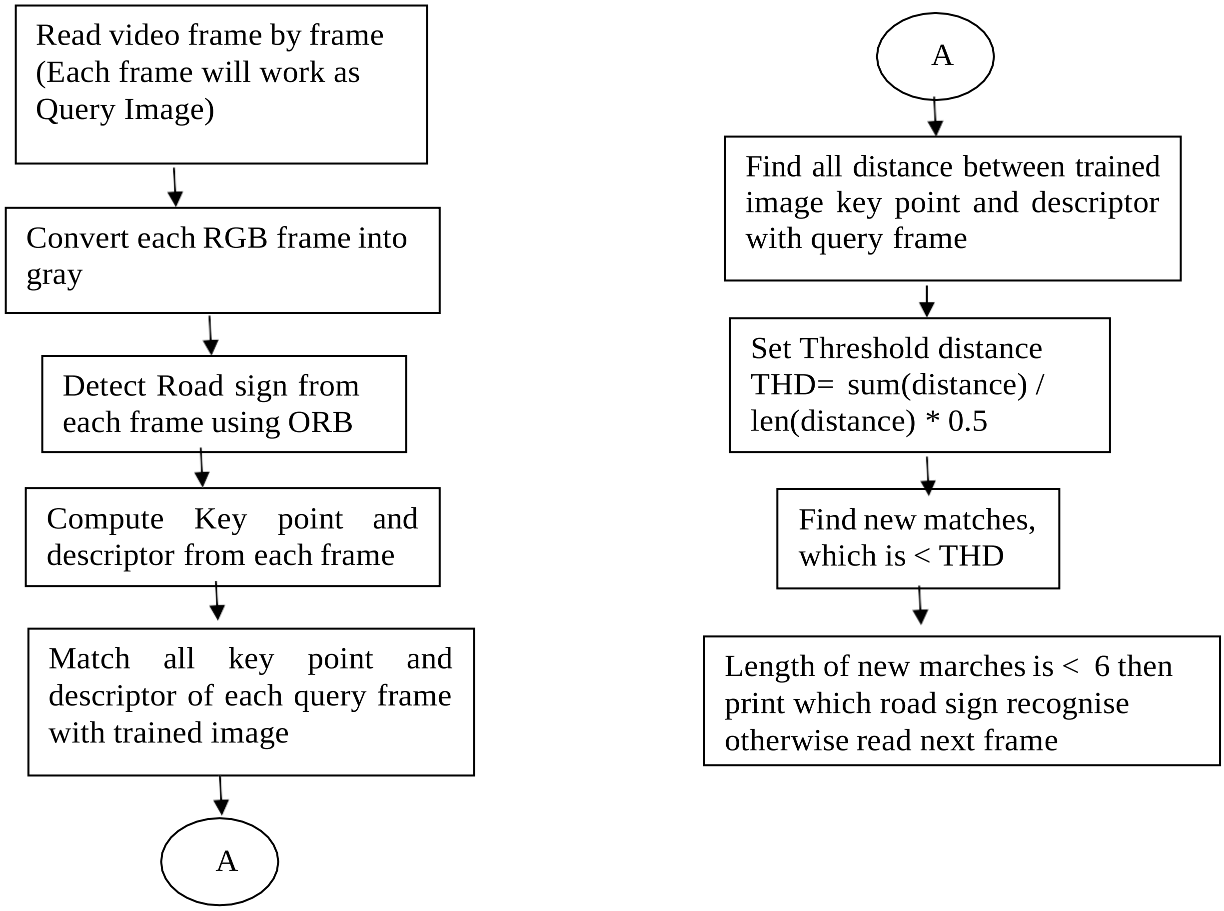
Phase1: Initialize Detector and BF matcher



Phase 2: Detect road sign from Train Image



Phase 3: Detect road sign from query image and match with train image and recognise which sign it is.



IV. RESULTS AND ANALYSIS

Implementation of ORB detection and BF matcher is shown in bellow figures. It will detect the all key points and descriptors of object from continuous live frame. BF matcher will match all key points and descriptors of each frame with each road sign of database.

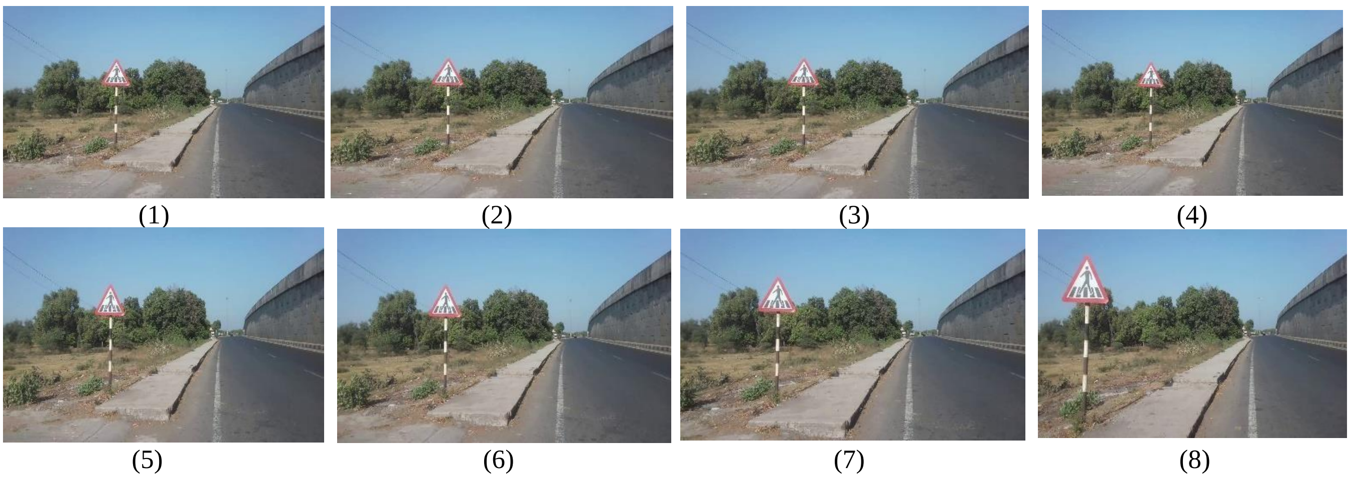


Fig: 5 Live road sign Video frames

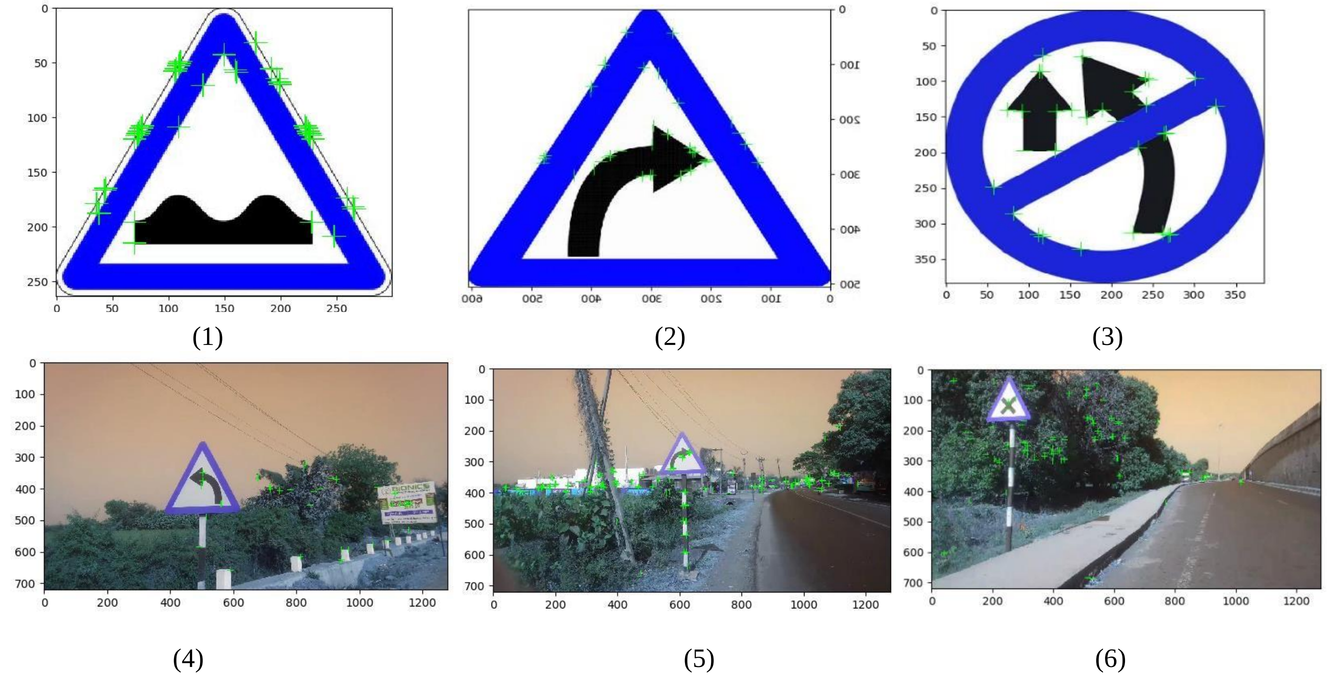


Fig:6 (1) –(3) Output of All descriptors and key point detected in Standard Indian Road sign database using ORB detector (4) – (6) Output of descriptors and key point of live video frames with different road sign.

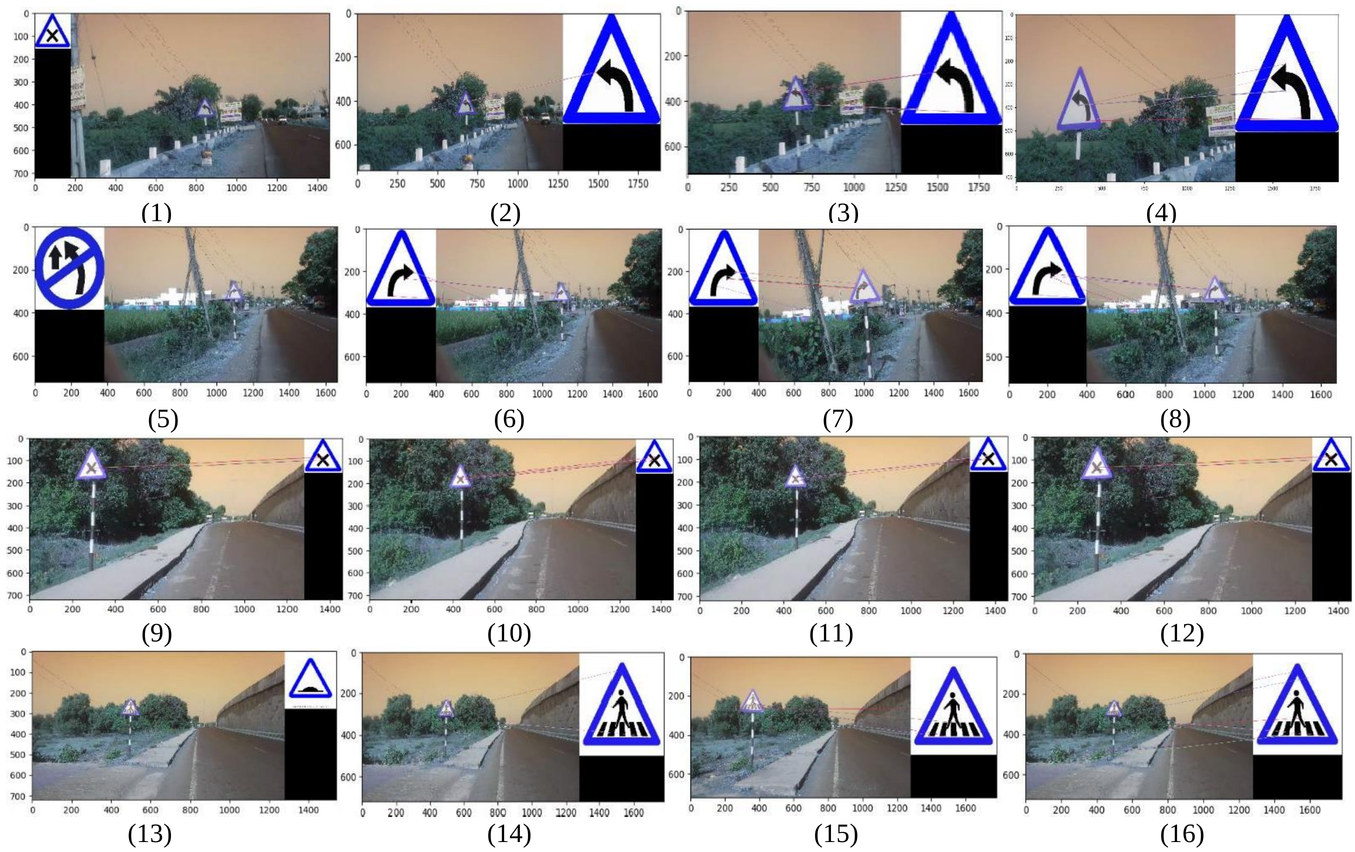
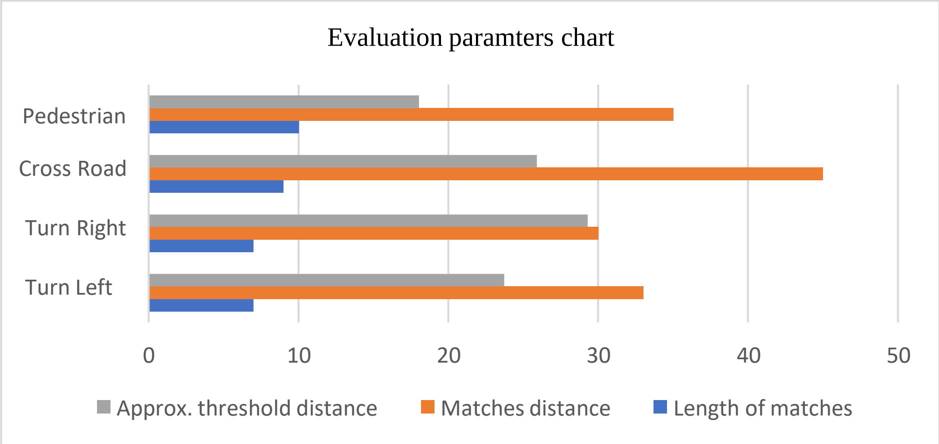


Fig:7 (1)No match found between live frame with left sign and different sign, (2)-(4) Descriptors and key point with match legth 2,4,6 respectively with Turn left road sign, (5) No match found between live frame with right sign and different sign, (6)-(8) Descriptors and key point with match legth 2,4,6 respectively with Turn right road sign, (9)-(12) Descriptors and key point match with legth 2,4,5,6 respectively with Cross Road road sign, (13) No match found between live frame with Pedestrian sign and different sign, (14)-(16) Descriptors and key point with match legth 2,4,6 respectively with Pedestrian road sign.

TABLE: 4.1 Evaluation parameter

	Sign is in Frame				Sign is not in frame			
Road Sign	**Approx. threshold distance**	**Matches distance**	**Length of matches**	**Best match**	**Approx. threshold distance**	**Matches distance**	**Length of matches**	**Detected best match**
Turn Left	21-25	60-80	1	NO	35-37	70-75	0	NO
	28	44-45	1/2/3	NO	33-30	60-70	0	NO
	23.7	33	7	YES	30	55-60	0	NO
Turn Right	30-35	60-80	1	NO	40	70-75	0	NO
	27-30	45-55	2/3	NO	35-40	60-50	0	NO
	29.3	30	7	YES	30-32	45-50	0	NO
Cross Road	31-34	60-90	1/2	NO	31-35	80	0	NO
	29-30	51-60	3/4	NO	28	60-64	0	NO
	25.9	45	9	YES	25-28	50	0	NO
Pedestrian	26-28	60-90	1/2	NO	40-42	90	0	NO
	29-31	40-50	1/2	NO	35	60-70	0	NO
	18	35	10	YES	28-32	45-50	0	NO



Accuracy of the system is calculated as

$$\text{Accuracy}=\sum_{i=1}^{N}\frac{\Sigma TD\times 100}{\Sigma FD+\Sigma TD}$$

Where TD- Ture detected sign and FD – false detected sign. The accuracy of this algorithm is 76.20% obtained.

IV. Conclusions

In this paper Real time Indian Road sign detection using ORB detector with key points and descriptor is proposed. To match detected sign with Indian Standard database BF matcher is used. This is efficient and new method for detection and matching of real time Indian Road signs. By Thresholding matched key point and descriptor successful Recognition of road sign analyzed in end of this paper. Pros of the given system is its Rotation and scale invariant. obtained accuracy of this system is 76.20%. This paper focus on Indian standard road sign data base. To train and test road sign most popular method of AI CNN(convolutional neural network) using numpy , tensorflow object detection API and building generative Adversarial network(deep learning) can be used. This is motivation to improve accuracy and efficiency of the system.

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