Autonomous Mobile Robot Navigation on Identifying Road Signs using ANN

Dr. Jharna Majumdar[1], Giridhar N R[2], Gagan P E[3]
[1] DEAN R&D Prof. and Head Dept. of MTech Computer Science & Engg., Head Center for Robotics Research,
[2] Research Associate, Center for Robotics Research,
[3] Student, Dept. of Electrical & Electronics Engineering,
Nitte Meenakshi Institute of Technology, Bangalore – 560 064, India

Abstract – **Road sign identification and classification is important for an autonomous navigating robotic vehicle. Many novel techniques were proposed in the past years to overcome these issues. The main objective of this research work is to implement it on a mobile robot and obtain a real time accuracy w.r.t Road sign classification. A Chinese road sign dataset is used for this purpose. Descriptors of this dataset is extracted from corner detectors like SIFT, SURF, ORB and fed into supervised learning techniques like SVM, L-R and ANN. Quality Metric Parameters like Recall, Precision and F1-measure, were used to determine the best method. LQR controller is used for the robot navigation. Road signs may be present in a clean or cluttered environment, to detect these signs in such unpredictable environments and feed it to classifier, Maximally Stable Extremal Regions (MSER) is used. On recognizing the road sign, mobile robot will navigate autonomously. On multiple experiments, the solution offered in this research work is very robust and accurate for real time applications.**

Keywords—**Corner Detectors, Scale Invariant Feature Transform (SIFT), Speeded Up Robust Feature (SURF), Oriented Fast and Rotated Brief (ORB), Support Vector Machines (SVM), Logistic Regression (LR), Artificial Neural Network (ANN), Maximally Stable Extremal Regions (MSER), Linear Quadratic Regulator (LQR).**

I. INTRODUCTION

Autonomous Navigation of robots and vehicles are given a lot of importance in the recent days as they provide Intelligent Transport Systems. With the help of Artificial Intelligence, Global Positioning System (GPS), smart sensors, these systems are one of the emerging technologies to look out for in the future. Road Signs provide visual information which are useful in navigation of robots and vehicles. An autonomous vehicle must be able to change its behaviour in real-time based on road signs present. Road sign detection and recognition is an important step towards autonomous driving systems. The main purpose of the road sign detection algorithms is to follow traffic laws and to avoid accidents.

II. RELATED WORKS

For the purpose of road sign identification, Amol Jayant Kale & Prof. R. C. Mahajan [1] have carried out a two-step procedure of detection by color segmentation and recognition by using Artificial Neural Networks in their paper. Stephen Karungaru, Hitoshi Nakano & Minoru Fukumi [2] in their paper have developed algorithms to detect stop signs using methods like template matching, genetic algorithms and Artificial Neural Networks for detection and classification. There are also methods for recognition and identification by using Capsule Networks -a deep learning architecture which is a modified form of Convolutional Neural Networks as illustrated by Amara Dinesh Kumar, R. Karthika and Latha Parameswaran [3] in their paper. Yan Lai, Nanxin Wang, Yusi Yang and Lan Lin [4] have discussed the use of Convolutional Neural Network Support Vector Machine (CNN-SVM) for classification in their paper. D V Filatov et al. [5] have discussed the use of morphological transformations such as dilation and erosion as preprocessing and using a feedforward neural network for classification. Michael Shneier [6] in his paper has described his method of classification by using rules for color and shape restriction for the signs to appear in only certain regions. And the classification is done by template matching. Hasan Fleyeh Mark Dougherty [7] have discussed the disadvantages of using image processing regarding the stability of obtaining color information at different times of the day and described many classifiers which can be used for recognition. Jack Greenhalgh and Majid Mirmehdi [8] have suggested a method of using MSER to detect areas containing traffic signs and then using Histogram of Oriented Gradients (HOG) to obtain features which are then classified using SVM, Random Forest and Multi-Layer-Perceptron

Many methods have been proposed about mobile robot's navigation using controller. LQR control and modelling of a skid steering mobile robot is described by Osama Elshazly and Hossam Abbas [9]. Anthony Mandow, Jorge L. Mart´ınez, Jesus Morales, Jos ´ e L. Blanco, ´ Alfonso Garc´ıa-Cerezo and Javier Gonzalez [10] in their paper improve the overall real time motion of a skid steering robot. Jianfeng Liao, Zheng Chen and Bin Yao [11] have looked at four wheel independently driven mobile robot for different ground conditions in their paper. For our research, we have made use of Traffic Sign Recognition Database (TSRD). Mobile robot used for this purpose is designed and developed in-house at Centre for Robotics Research, NMIT. On recognizing the road sign, the robot must be able to act independently, which is achieved through Linear Quadratic Regulator (LQR) Controller. The control law is obtained on solving Algebraic Riccati Equation (ARE). The controller in combination with the traffic sign detection algorithm helps the mobile robot in smooth navigation. Experiment based observations reveals that our solution is very robust.

III. CORNER DETECTORS FOR ROAD SIGN IDENTIFICATION

Corner is an interest point where there is an intersection of two edges, where edge is an abrupt change in image intensity. Corners can also be used in restoring image information. Many novel methods have been proposed to detect corners in an image like Harris operator, Kanade-Lucas-Tomasi operator which are simple, efficient, invariant to rotation, scale and fast to compute. They are the important local features present in an image. In this paper, for corner point detection and corner feature extraction, we have made use of Scale-Invariant Feature-Transform (SIFT) [12], Speeded Up Robust Feature (SURF) [13] and Oriented Fast and Rotated Brief (ORB) [14] corner detectors. As it is widely known and in Ebrahim Karami et.al [15] research paper it is proven that ORB is computationally faster and SIFT performs the best. Descriptors present in the database is extracted and fed into supervised learning techniques which are explained in section IV. For our research work, we have made use of TSRD dataset, which contains 6164 traffic signs 57 sign categories.

IV. SUPERVISED LEARNING TECHNIQUES

In the present paper, we have incorporated supervised learning techniques as our training dataset are labelled. Supervised learning techniques analyses the training data and will give an inferred function which can be used to map new data. The classification techniques incorporated are:

- Support Vector Machine (SVM)
- Logistic Regression (LR)
- Artificial Neural Network (ANN)

A. Training Data Set

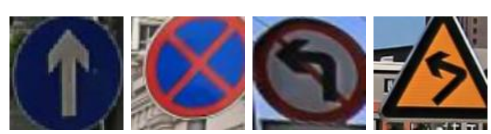
The training data set used is off Chinese Traffic Signs. It contains a total of 57 sign categories i.e. 57 classes. The three corner detectors used are SIFT, SURF and ORB. For each image in each class, best 5 key-points are obtained as well as their descriptors. Number of descriptors for each key-point is:

- SIFT – 128 Descriptors per key-point
- SURF – 64 Descriptors per key-point
- ORB – 32 Descriptors per key-point

From each image which belongs to its respective class, best 5 key-points are extracted. As it is a supervised learning, adding noisy descriptors to the classifier will not yield good results, it would increase the loss value and decrease the accuracy. Thus, we went with choosing best 5 key-points. Out of 6164 images, 67% (4170) of the dataset is used for training and 33% (1994) is used for testing. These testing images remain completely neutral to training. SIFT, SURF and ORB corner detectors are used to extract their respective descriptors. This is used as input to our three supervised learning techniques. To find out which among these techniques give best result, in-order to implement it on a mobile robot, we have made use of quality metric parameters like precision, recall and f1-score to determine the same.

B. Linear Classifiers

To distinguish the descriptors obtained from all classes when plotted in 2D, it is required to partition or draw a line between them. This is done to get a decisive boundary between classes. So, in 2D, a single line separates descriptor space into ‘n’ classes. Support Vector Machine (SVM) and Logistic Regression (LR) are the linear classifiers that we have incorporated. Feeding all the classes (57 classes) into a single classifier will result in a lot of hyperplanes and weights to distinguish the classes. The accuracy will gradually decrease as there are more classes and it adds a lot of noise. This is also not the right approach to train the classifier. As we would be finally integrating it on a mobile robot, which will look at the given road sign and navigate accordingly, we use color based linear classifier. Our entire dataset consists of road signs which belong to four different colors; blue, red, yellow and blue-red (presence of both red and blue)



(a) (b) (c) (d)

Fig 1. (a) Blue, Blue-Red, Red, Yellow are the different types of road signs with four different colors.

The training dataset are divided into 4 main classes based on color, as shown in Fig 1. In *Training Data set,* we have shown how the descriptors are extracted. These descriptors are fed into the linear classifiers, i.e. SVM and LR. This is done for all the 4 main classes.

SVM (Fig. 2) makes use of the complete data set to fit the hyperplane between the classes w.r.t to the descriptor values. Logistic Regression on the other hand is trained for mini-batches from the dataset. It aims at minimizing the expected loss by performing gradient descent. Linear SVM is used rather than Gaussian SVM. The result of linear classifiers is shown in section V

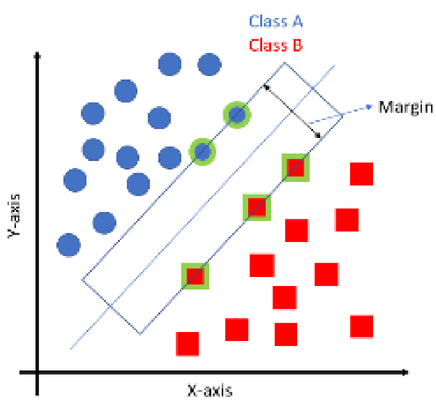


Fig 2. Representation of Support Vector Machine

C. Artificial Neural Network

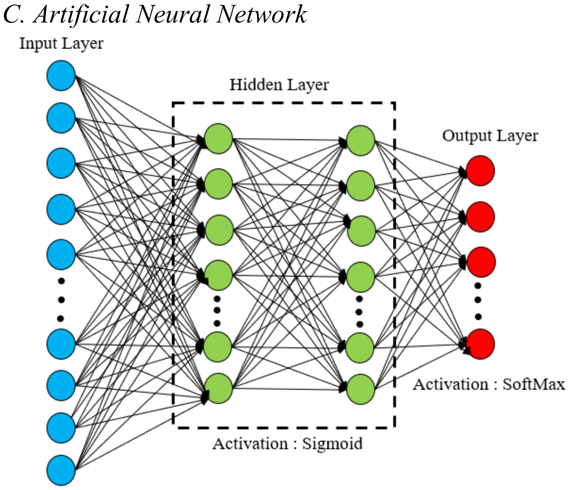


Fig. 3. Architecture of 3 layer-ANN

Fig. 3. shows the architecture of Artificial Neural Network (ANN) that is incorporated for our purpose. Here the entire architecture and functionalities is hard-coded in python without the use of Deep Learning modules. As mentioned in section IV-A, Training Data set, we are using best 5 key-points in each image. Here the number of input layers depends on the corner detector that is used. On using SIFT, which has 128 descriptors for one key-point, there are a total of 128 x 5 = 640 descriptors. So, the number of neurons in input layer will be 640. Similarly, for SURF and ORB, it is 320 (64 x 5) and 160 (32 x 5) neurons respectively. It is a 3-layer ANN that is been used with 2 hidden layers and 1 output layer. The number of neurons in each hidden layer is 50. In the preceding part, we have explained the reason for choosing 50 neurons in both the hidden layers. In section IV – B, we have explained our approach towards about 4-class classifiers. So, we have 4 ANN's, one for each color-class. The number of road signs (sub-class) in each color-class is mentioned below.

- Red - 22
- Blue - 13
- Yellow - 20
- Red-Blue - 2

This forms the number of neurons in the output layer. The different activation functions required to activate a neuron are:

- Sigmoid function
- Hyperbolic Tangent Activation Function (TanH)
- SoftMax function
- Re-LU function

Different type of combinations was performed on number of neurons to present in the hidden layer along with the activation functions. On analysing the precision, recall and f1-score of them, hidden layer having 50 neurons each with activation function Sigmoid and output layer with activation function SoftMax gave the best result.

Sigmoid Function $\sigma(z)$

$$\sigma(z) = \frac{1}{1+e^{-z}};\; z = \sum_{i=1}^{m} w_i x_i \; + bias$$

The output of the sigmoid function is between 0 and 1. To activate one of the hidden layer's neuron, the sigmoid neuron's output should be greater than or equal to 0.5.

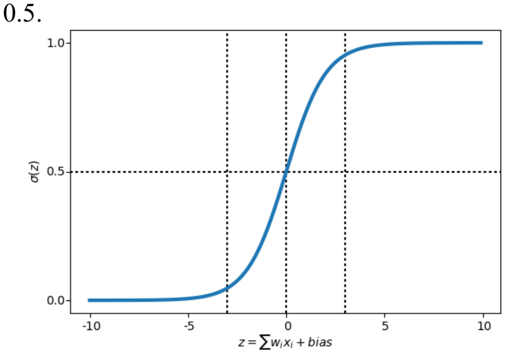


Fig. 4. Pictorial Representation of Sigmoid Function

SoftMax Function $\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_j}}$

The output of SoftMax function tells the probability of any of the classes that are true. It squashes outputs of each unit to be in between 0 and 1; and sum of the outputs will be equal to 1. The neuron with the maximum probability value is the output class.

Error and Loss Function $J(w)$

To compute the difference between desired output and predicted output, loss function is used. For our purpose we have made use of Cross-Entropy function. As we have more than two classes as our desired output, we calculate loss for each of the class label and sum the result. A cost function is computed to find out the relationship between input X and its corresponding output y. Cost function is a measure of how wrong the model is in terms of its ability to estimate the relationship between input X and its corresponding output y. $Cross\_Entropy = -\sum_{c=1}^{M} y_{o,c} \log(p_{o,c})$

Backpropagation

For a Neural Network to learn its weights and biases, gradient descent algorithm is needed. Backpropagation [16] is used to compute such gradients. In the recent years, it's a workhorse of learning in neural networks.

Optimizer

To update the weights and maintain the value of cost function minimal, optimizers are used. For our research work, ADAM's optimizer [20] is used which computes adaptive learning rates for every parameter on estimating first and second moments of the gradients.

With the help of above-mentioned functions, the hyperparameters used for supervised learning are

- Learning rate – 0.001
- Epoch – 150
- Batch Size - 128

V. RESULTS – TESTING

There are 3 supervised learning techniques, SVM, LR and ANN. There are 4 main classes; Red, Blue, Yellow and Red-Blue. There are 3 descriptors used for training, SIFT, SURF and ORB. In this section, results of testing are shown below in table format. For each main class, it will be a combination of 3 supervised learning techniques with 3 descriptors. Based on the value of recall, precision and f1-measure, best combination is taken forward for implementation on mobile robot for that specific main class.

TABLE I

Quality Metric Parameter values for Red-Blue Class with 2 sub-classes in Testing Phase

Class: Red-Blue; Descriptor: SIFT									
	SVM			LR			**ANN**		
Classes	Precision	Recall	F-1	Precision	Recall	F-1	**Precision**	**Recall**	**F-1**
01	0.92	0.88	0.90	0.81	0.86	0.84	**1.00**	**1.00**	**1.00**
02	0.60	0.72	0.65	0.59	0.49	0.53	**1.00**	**1.00**	**1.00**
Class: Red-Blue; Descriptor: SURF									
	SVM			LR			ANN		
Classes	Precision	Recall	F-1	Precision	Recall	F-1	Precision	Recall	F-1
01	0.92	0.95	0.93	0.94	0.55	0.69	0.78	1.00	0.87
02	0.67	0.56	0.61	0.39	0.89	0.54	0.89	1.00	0.94
Class: Red-Blue; Descriptor: ORB									
	SVM			LR			ANN		
Classes	Precision	Recall	F-1	Precision	Recall	F-1	Precision	Recall	F-1
01	1.00	0.86	0.93	0.7	0.47	0.56	0.97	0.99	0.98
02	0.62	1.00	0.77	0.53	0.75	0.62	0.98	0.96	0.97

From Table – I, results of ANN-SIFT gave the best results for BLUE-RED class. Similarly, on analysing of results on all classes, ANN-SIFT gave the best results on the testing dataset.

TABLE II

Timing Analysis for Red-Blue Class with 2 sub-classes in Testing Phase

Class: Red-Blue; Descriptor: SIFT			
	SVM	LR	ANN
Classes	Time(s)	Time(s)	Time(s)
01	0.072	0.031	0.000558
02	0.052	0.022	0.00052
Class: Red-Blue; Descriptor: SURF			
	SVM	LR	ANN
Classes	Time(s)	Time(s)	Time(s)

01	0.0906	0.0643	0.00071
02	0.014	0.0582	0.00043
Class: Red-Blue; Descriptor: ORB			
	SVM	LR	**ANN**
Classes	Time(s)	Time(s)	**Time(s)**
01	0.010	0.0147	**0.00034**
02	0.027	0.0177	**0.00032**

From Table-II, the timing analysis shows that ANN-ORB has the least execution time. Yet the accuracy of ANN-SIFT is high hence it is used for real time implementation.

VI. MOBILE ROBOT

The mobile robot used in this research work, is designed and developed in house at Centre for Robotics Research Centre (CRR), NMIT. For the mobile robot to navigate we have made use of LQR controller.

Fig. 5. Mobile Robot designed and developed in House

To avoid the mobile robot to clash with any obstacles, LV Maxsonar EZ sonar sensor is used.

*A. Linear Quadratic Regulator Controller (LQR)*LQR controller is a type of optimal controller. These types of controllers are used to control a system by reduction of a cost function. This specific case of controllers is designed where the system is defined by linear differential equations and the cost is quadratic in nature. Hence it is called Linear Quadratic Regulator. It is a type of state space controller. For an SSMR based on the modelling the state of the system is represented by $= [V_x\ \omega]^T$, where V_x is linear velocity and ω is angular velocity. The input to the system is given by $U = [V_1\ V_2]^T$. Even though the robot is four wheeled we only need two voltages as input since the wheels on each side are assumed to be coupled. The state space model is given by $\dot{X} = AX + BU; Y = CX$. The control requires two parameters Q and R which decide the relative importance of state X and input U. The cost function is $J = \frac{1}{2}\int_0^{\infty}(X^TQX + U^TQU)dt$. The control law is given by $U = -K * X$; where $K = R^{-1}B^TP$; which is obtained by solving Algebraic Riccati Equation (ARE).

B. LV max sonar EZ sonar sensor

Fig. 6. Sonar Sensor

Sonar sensor is used to detect and ranging any obstacle along the path of the robot. If any pedestrian or obstacle appears in the path of the robot, based on the reading obtained from the sensor the robot checks its left or right to decide the optimal path for movement.

VII. INTEGRATION

In section IV, we have shown that we have four classifiers based on color, i.e. Red, Blue, Yellow and Red-Blue. As ANN-SIFT gave us the best results for all the four classifiers, it is important and necessary to feed only the Region of Interest as Input to the network. In Fig. 7, there is an example of how the road sign will be placed. The background may be clean or cluttered. Here we have considered cluttered background as an example and will show how to extract only the ROI to feed it to the network. After obtaining the ROI, it is fed into the respective classifier, and based on its output, corresponding signal will be sent to LQR controller to perform the desired action.

Fig. 7. A scenario of how the sign will be placed.

A. Extracting Region of Interest

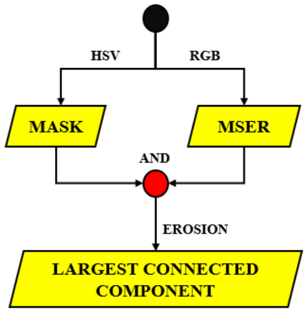


Fig. 8. Extracting Region of Interest

Fig. 8. shows the flow that is incorporated to extract the Region of Interest. The input scene is converted to HSV color format [17]. As we already know that the four classifiers are based on color, we perform masking on HSV scene, Fig. (b). In this case RED masking is performed. Maximally Stable Extremal Regions (MSER) [18] are the regions present in the image, which are stable and invariant connected component of some level sets of the scene, Fig. 8(c). Fig. x(d) shows the output obtained on binarizing the regions obtained from MSER. On performing AND operation on the outputs of Fig. x (c) and (d), Image shown in (e) is obtained. To remove speckles of noise present, Erosion operation is performed. MSER, by default gives us stable connected component. On the eroded image, Largest connected component is extracted, Fig. x (f) and that is our ROI, Fig. x (h).

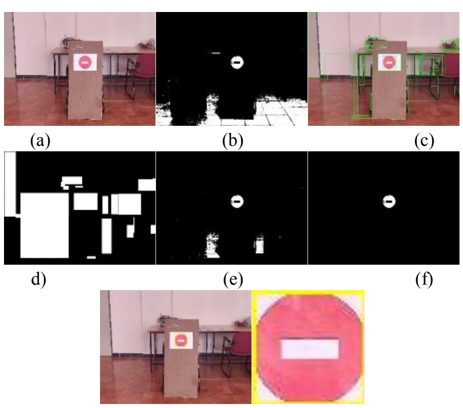


Fig. 9 (a) Input Image, (b) Red-Mask (c) MSER (d) Binarized MSER (e) AND Operation on Mask and Binarized MSER (f) Largest Connected Component (g) Mapping to Actual Image (h) Region Of Interest

B. Autonomous Robot Navigation on Identifying Road Signs

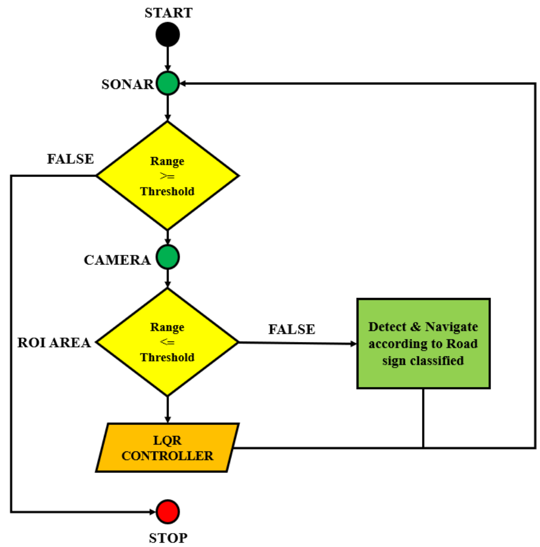
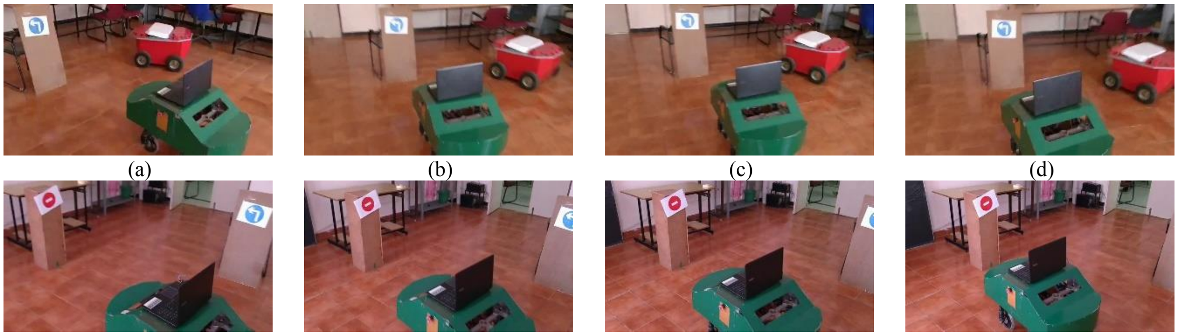


Fig. 10. Flow followed on Integrating with Mobile Robot

LQR Controller is used for navigation. It is implemented on MBED [19]. There are two sensor inputs to robot. One is the Camera and the other being Sonar. Camera is used to detect road sign and Sonar is used to detect any obstacle in the robot's path. The end point is reached when STOP road sign is detected. If any obstacle, is present in the robot's path, Sonar is used to obtain the optimal path for movement by moving the robot to its right and left. Camera on the other hand is used to grab frames to detect road sign. In the previous section, it is shown how to extract ROI. On extracting ROI, if its aspect ratio is in between 0.7 - 1.3 and it occupies at least 10% of the image area, it is fed into the network for identifying the road sign. The reason for specifying such thresholds is to prevent any false ROI's to be fed into the network. As we already know the information about the color of road sign, which is obtained when masking is done, it is easy to feed it into the respective ANN. The same flow is represented pictorially in Fig. x.

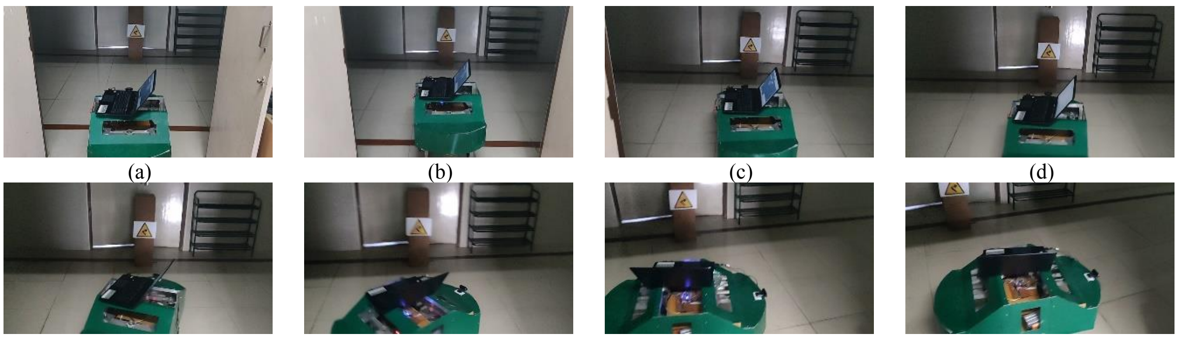
VIII. RESULTS

In this section, autonomous mobile robot navigation on classifying road signs is presented. The ANN architecture discussed in section iv is implemented on the mobile robot with LQR controller, section Vi. There are three video sequences that are presented below, Fig. 11, Fig. 12 and Fig. 13.



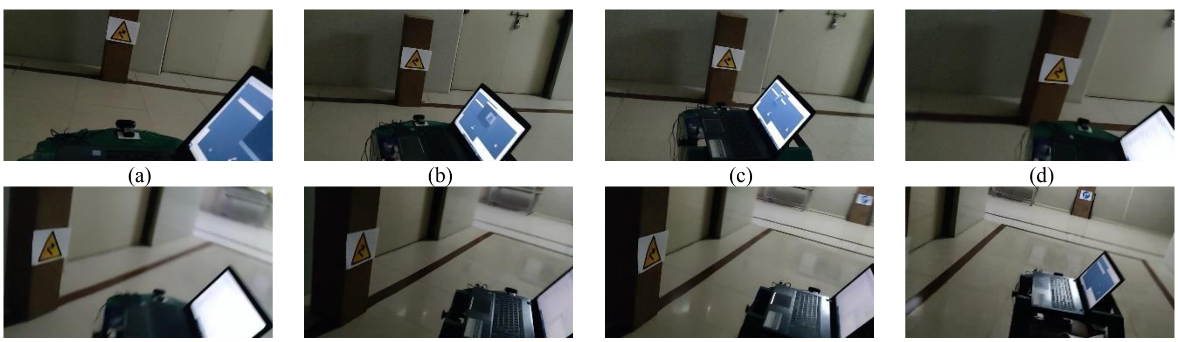
(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 11 Autonomous Robot Navigation – Video Sequence 1 (a) Frame No 18 (b) Frame No 28 (c) Frame No 44 (d) Frame No 52 (e) Frame No 69 (f) Frame No 76 (g) Frame No 97 (h) Frame No 118



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 12 Autonomous Robot Navigation – Video Sequence 2 (a) Frame No 11 (b) Frame No 25 (c) Frame No 29 (d) Frame No 38 (e) Frame No 44 (f) Frame No 56 (g) Frame No 68 (h) Frame No 78



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 13 Autonomous Robot Navigation – Video Sequence 3 (a) Frame No 5 (b) Frame No 16 (c) Frame No 21 (d) Frame No 26 (e) Frame No 39 (f) Frame No 43 (g) Frame No 52 (h) Frame No 58

IX. CONCLUSION

In this research work, we have proposed an architecture of ANN which takes descriptors from SIFT to train on TSRD dataset. On comparing the QM Parameters as shown in Table I, ANN-SIFT gave better results than LR and SVM. The LQR controller used for mobile robot's navigation along with ANN-SIFT for road sign classification gave almost real time accuracy. As we are making use of Chinese Dataset, we are restricted to categories of road sign. We are limited to four color class categories. So there exists a dependency on color of road sign. Way forward in computer vision would be to make it independent of color-class category by making use of deep neural network models. Way forward in control system would be to build a stable controller or replace the controller with image-based navigation using Convolutional Neural Network.

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