Vol. 4, No. 1 | January – June 2021

Urban Road Traffic Sign Detection & Recognition with Time Space Relationship Model

Bhutto Jaseem Ahmed[1], Qin Bo[1], Qu Jabo[1], Zhai Xiaowei[1], Abdullah Maitlo[2]

Abstract:

Detection and recognition of urban road traffic signs is an important part of the Modern Intelligent Transportation System (ITS). It is a driver support function which can be used to notify and warn the driver for any possible incidence on the current stretch of road. This paper presents a robust and novel Time Space Relationship Model for high positive urban road traffic sign detection and recognition for a running vehicle. There are three main contributions of the proposed framework. Firstly, it applies fast color-segment algorithm based on color information to extract candidate areas of traffic signs and reduce the computation load. Secondly, it verifies the traffic sign candidate areas to decrease false positives and raise the accuracy by analysing the variation in preceding video-images sequence while implementing the proposed Time Space Relationship Model. Lastly, the classification is done with Support Vector Machine with dataset from real-time detection of TSRM. Experimental results indicate that the accuracy, efficiency, and the robustness of the framework are satisfied on urban road and detect road traffic sign in real time.

Keywords: *Traffic Sign Detection & Recognition; Time Space Relationship Model; Fast color Segmentation and Compression; Intelligent Transportation System*

1. Introduction

As an Intelligent Transportation System (ITS) road traffic sign detection and its recognition are playing an increasingly instrumental role for providing road safety to the drivers. Autonomous detection and recognition of traffic sign plays an extremely vital role in Advance Driver Assistance System (ADAS) of possible danger such as pedestrian crossing or speed limits.

On-road traffic sign/symbols exhibits several distinguish features i.e., Shape and Color that can be used to detect and recognize them. With their composition of specific Shape, Color and having the text or symbol imprinted over the circular, triangular or rectangle board with background colors like Red, Yellow, and Blue; it has become important to detect and recognize them in an effective way. But as the traffic signs have their orientation upright and facing the camera, hence rotational and geometric distortion is limited. The availability of knowledge about traffic symbols (shape and color) as a source be used to categorize into specific groups after carefully examining and analyzing various factors that can hinder in effective detection and recognition of the traffic signs. These factors may include perspective variations, different levels of illumination, twilight, fog, shadowing, obstacles in scene, motion blur, weather and affects etc. which can lead to limited scope of detection and recognition.

[1] Department of Computer Science & Technology, Ocean University of China, Qingdao, China
[2] Computer Science Department, Shah Abdul Latif University Khairpur, Pakistan.
Corresponding Author: jaseem.bhutto@gmail.com

To deal all this, accuracy and efficiency of the detection system is must, as a single misclassified or undetected sign can be cause of the unfavorable impact for the driver. There had been an extensive research in the said field, but a real-time system had not been developed yet, which could hinder the urban road accidents.

The traffic sign detection systems, however, can be classified into either or both scenarios; Shape based, and Color based. Different types of color spaces have been used which includes HIS-HSV [1] [2], YUV [3] or Gaussian Color Model [4] to define traffic sign region as visual features. Similarly, the shape features, such as Hough Transform [5], Local Contour Pattern [6] or Local Binary Pattern [7] have also been used. Additionally, many latest developments in computer vision [8] [9] have focus on the images, based on three dimensional (3D) reconstructions.

Semantic Texton Forests and image-based 3D points clouds have been used for categorization, segmentation, and recognition of highway assets [10]. Support Vector Machine (SVM) and Semantic Texton Forests were proposed by [10] [11] and are being used to recognize the traffic signs. The vertical traffic sign classification and recognition is focused by [12] (retro-reflective) for their various functionalities (danger, give way, indication etc.). The recognition was also achieved by adapting Gaussian-Bernoulli Deep Boltzmann (GBDB) machine model based on the hierarchal classifier [13]. Global strategy for the detection can be used which is based on filtering the noise point by distance setting & threshold elevation and the segmentation region of traffic sign can then be obtained.

This paper introduces a video-based traffic sign detection and recognition system / framework, which could be embedded into mobile intelligent system for Intelligent vehicles. The system is based on continuous video of the on-road vehicle movements. This is a seed to mobile intelligent system, which can realize real-time traffic sign detection and recognition accurately and efficiently in the complex urban road environment.

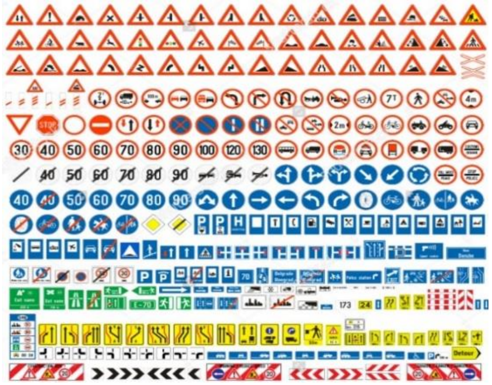


Fig. 1. *Different varied types of Traffic Signs* (Source: European traffic signs collection. danger, mandatory & signs of obligations)

The rest of this paper is organized as follows: Section 2 briefly shows the in-depth step by step process of proposed system. In Section 3, Fast Segmentation and Compression Algorithm and Time Space Relationship model has been discussed in detail. In Section 4, we analyze the experimental data. In Section 5, we discuss the process of dataset training, classification, recognition, and comparison of results using TSMR and other literatures. Finally, we conclude the paper in Section 6 and forthcoming recommendations are given in section 7.

2. Proposed Architecture

Fig. 2 is the proposed architecture which gets the video sequence and set region of interest first and then Fast Segmentation and Compression Algorithm is applied, which reduces the computation load and increases the efficiency. Later, Time Space Relationship Model (TSMR) is used on video sequence with HOG feature to track and detect the object in sequence of video. Finally, SVM is used to classify and recognize the traffic sign.

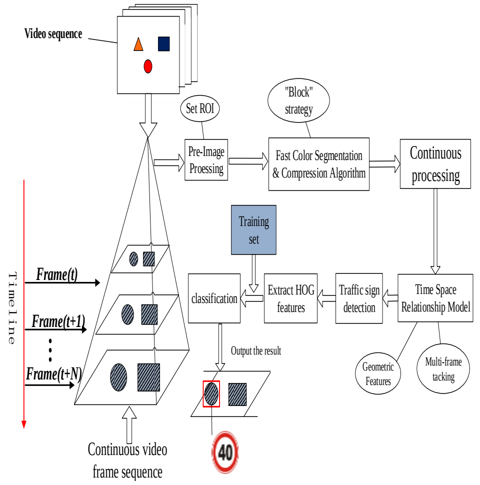


Fig. 2. *Detection & Recognition Architecture*

3. Algorithm and Model Design

The proposed algorithm is used to segment the image quickly by using the compression algorithm to get the binary image of the traffic sign candidate region. The fast color segmentation and compression algorithm stores the pixels that meet the segmentation threshold into compressed binary image according to the block model. The color segmentation threshold parameters are optimized for the actual urban road scenes, the output images are compressed by the "block" strategy and connected regions are merged then.

3.1. Fast Color Segmentation and Compression Algorithm

- **Step 1**: Convert RGB image into HSV image $I(x, y)$;
- **Step 2**: Set all the pixels (x_i, y_i) in image I to white if they satisfy the segmentation threshold of a color, that is, $\forall(x_i, y_i) \in I(x, y)$.

$$Color\ (x_i, y_i) = \begin{cases} 255, if\ H((x_i, y_i), S(x_i, y_i), V(x_i, y_i) \\ \quad all\ are\ satisfied. \\ \quad 0, Otherwise \end{cases} \tag{1}$$

Where *Color* represents a binary image divided for a certain color segmentation

- **Step 3**: The image I is divided into $M \times N$ of size $m \times m$ sub-image blocks of $A_{i,j}(i = 1, 2, 3 \ldots, M; j = 1,2,3 \ldots, N)$. The correspondence between image $Color$ and the segmentation result image $Binary$ satisfies:

$$Binary(i, j) = \begin{cases} 255, & if\ Count_{i,j} \geq thC \\ 0, & if\ otherwise \end{cases} \tag{2}$$

The Formula 2 $Count_{i,j}$ represents number of white pixels in sub-image block $A_{i,j}$, the thC is the threshold. After this step, the original image I is segmented and compressed by an image size of $m \times m$ $Binary$ image. Fig. 3 shows the mapping relationship between *Color* and *Binary*.

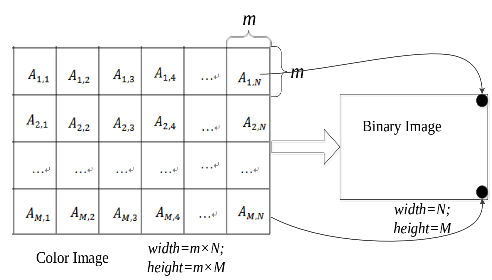


Fig. 3. *Color and Binary application mapping*

- **Step 4:** The adjacent areas are merged, and the adjacent connected areas in the image $Binary$ are combined into one region to prevent the traffic area sign from being missing due to change of illumination conditions, and the integrity of the traffic mark area is ensured to obtain the image segment.
- **Step 5**: Fig. 4 shows the Output of traffic sign segmentation image.

a) Region of Interest *(b) HSV images*

(c) Red segmentation. *(d) Region consolidation*

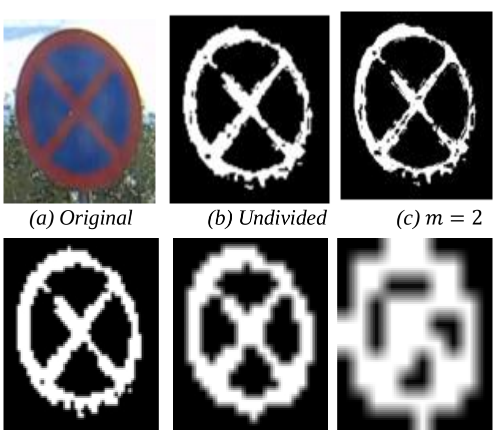
Fig. 4. *Segmentation & Compression Algorithm*

3.1.1. Block Size Selection Strategy

In Step 3, the image I is divided into $M \times N$ sub-image blocks of size $m \times m$. The selection of m and the selection threshold of thC will affect the segmentation result image $Binary$.

3.1.1.1. Selection of value of block size M image.

Fig. 5 shows the segmentation results of original image 5 (a) at m = 1, 2, 4, 8 and 16, respectively. Comparing Fig. 5. if m≤8 the segmentation shape, result basically maintains the original shape. If the value of m is too large, the area of the segmented image is too large or too small, which will affect the detection result. If the value of m is too small, the effect of reducing the amount of data by compressing the image will not be achieved.



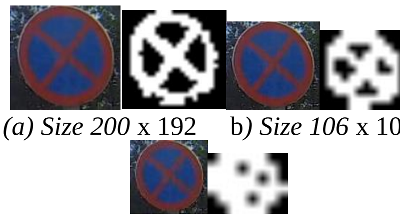
(a) Original *(b) Undivided* *(c)* $m = 2$

(d) $m = 4$ *(e)* $m = 8$ *(f)* $m = 16$

Fig. 5. *m value of traffic sign segmentation*

If value of m is fixed, the size of the original image will also have some influence on the image. Fig. 6 shows the effect of m=8 as an example on the segmentation of different size images.

If the value of m is too large, it will contain more noise zones and the error will fluctuate greatly. If the value of m is too small, there is possibility of missing traffic sign. If the m value is fixed, the image size will have an impact on the segmentation and improves efficiency. The paper will take m=4 to improve accuracy and efficiency.



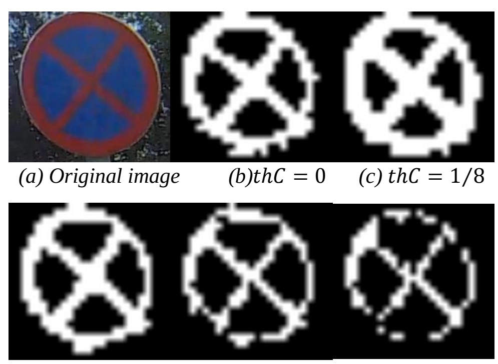
(a) Size 200 x 192 b*) Size 106* x 104

c) Size 54 x 61

Fig. 6. *Segmentation result of size* $m = 8$

3.1.1.2. Selection of screening threshold thC.

As shown in Fig. 7 the size of thC in (e) and (f) is too large, which causes the fracture of the traffic sign area and affects the detection of traffic signs. The general segmentation to ensure the normal traffic area, select the $thC = 1/8$ or $thC = 1/4$. As shown in Fig. 7.



(a) Original image *(b)*$thC = 0$ *(c)* $thC = 1/8$

(d)$thC = 1/4$ *(e)*$thC = 1/4$ *(f)* $thC = 2/3$

Fig. 7. *Different segmentation threshold thC with* $m = 8$

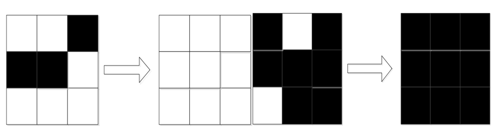
3.1.2. Adjacent Region Merging

As shown in Fig. 4 (d), when traffic signs are segmented, the traffic sign area will be broken into several adjacent small, connected regions due to the change of illumination condition, the size of block *m* and the *thC* of screening threshold. At this point, adjacent areas need to be merged. The specific implementation is as shown in Fig. 8.

- **Step 1:** In the image Binary, the size is set as $M \times M$ pixels (M generally takes 2 or 3, $M = 3$ as an example in this case). $Num(White)$represents the number of white pixels in the set, and thR is the merge threshold parameter. If $Num(White)$and thR satisfy the relation of Formula (3)

$$Num(White) \geq thR \tag{3}$$

The white pixel points of the set belong to the same connected area, and the black pixel points in the set are modified to white. If the Formula (3) is not satisfied, the white pixel point in the region is identified as an isolated point, and it is set to black, and Fig. 8 represents the process.



(a)Satisfies formula (3) *(b) doesn't satisfy formula (3)*

Fig. 8. *Step 1 Processing for region merging.*

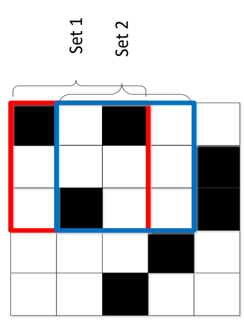


Fig. 9. *Step-2 Traversal process of region merging.*

- **Step 2:** As shown in Fig. 9, traverse the Binary image until the merge is complete.

3.2. Time Space Relationship Model

There are limitations of Traffic Sign Detection (TSD) based on a Single Frame [14]. Due to camera's point of view, different angles and other factors, the specific location of the Traffic Sign (TS) in the image plane is uncertain [15]. And the tilted, distorted, broken TS leads to irregular connected areas. Thus, TSD based on a single frame has high false positive and low robustness. Therefore, based on the continuous change relationship between the time and space position of traffic sign in the continuous sequence of traffic scenes, a Time Space Relationship Model is proposed to detect and verify the traffic sign candidate regions furthermore. Fig. 10 demonstrates the on-road side view scene.

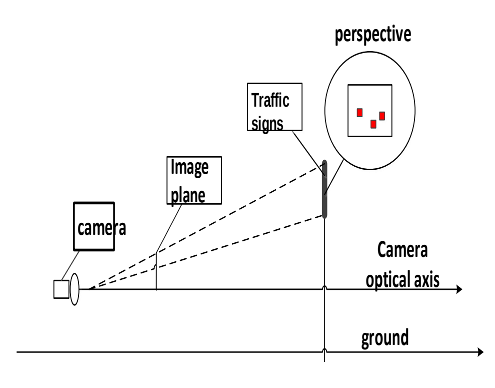


Fig. 10. *Side view of the scene*

Fig. 11 exemplifies the structural relationship among traffic sign, image planes and camera at a certain time. As seen in Fig. 11, ***f*** is focal length of camera. ***d*** is the vertical distance between Image Plane and Traffic Sign. ***L*** is the size of the Traffic Sign on the Image Plane. S is the actual size of Traffic Sign. Note that ***L*** and ***S*** stand for the perimeter or area of Traffic Sign.

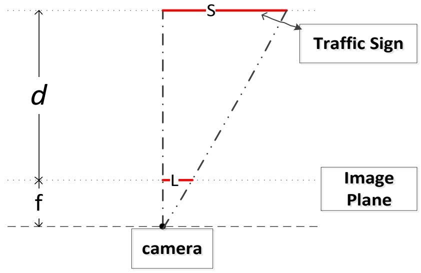


Fig. 11. *Spatial constraints among traffic sign, image planes and the camera*

According to similar triangle principle, drawn Formula (4),

$$\frac{f}{f+d} = \frac{L}{S} \tag{4}$$

As the value of f is much smaller than the value of d, the formula (4) can be simplified into formula (5):

$$\frac{f}{d} = \frac{L}{S} \tag{5}$$

Thus, size of traffic sign on image plane L is:

$$L = \frac{f \cdot S}{d} \tag{6}$$

As the distance d between traffic sign and the camera decreases, the size L of the traffic sign in the image increases accordingly. At the same time, traffic signs in the image position begin to move up.

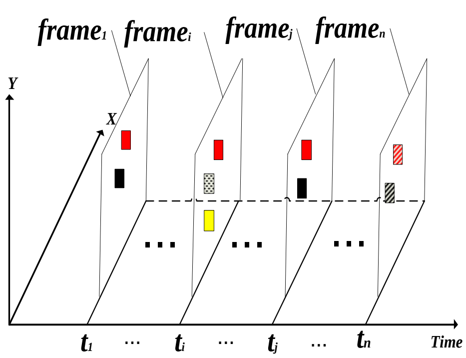


Fig. 12. *Framework of traffic sign detection and recognition based on TSRM.*

In a certain period of time in the $\Delta T(t_1, t_2, \dots, t_n)$, the size and position of the traffic sign area L in the continuous image sequence of the traffic scene shows a continuous change. There will be no sudden appearance or disappearance of traffic signs, but a continuous process of change. Set L_{max}, L_{min} for traffic signs to meet the minimum and maximum size of the detection. every frame of image corresponds to a connected region $R'_i(i = 1,2, \dots, n)$ in the period of $\Delta T(t_1, t_2, \dots, t_n)$, and any traffic sign detection candidate area $l_1 \in R'_1$, if the area appears in consecutive multi-frames, it is determined that the area is a traffic sign area; otherwise, it is determined as a noise area. Specific findings based on the following:

According to the continuous change of traffic signs in the sequence of traffic scene images, the expression of a candidate region in each frame which is set in $\Delta T(t_1, t_2, \dots, t_n)$ is $L(l_1, l_2, \dots, l_n)$. The sizes of $l_i(i = 1,2, \dots, n)$ are all the same or nonexistent (undetected).

Suppose L is in the time period $t_i, \dots, t_j (1 \le i < j \le n, M = |j - i + 1|)$. If the connected region set $R'_k\ l_k(i \le k \le j)$, marking its state as 1, Otherwise 0, then the state sequence corresponding to l_k in time $t_i, \dots, t_j$ is $F[f_i, f_{i+1}, \dots, f_j]$, where

$$f_k = \begin{cases} 1, if\ l_k\ exists \\ 0, otherwise \end{cases} \quad (i \le k \le j) \tag{7}$$

In the state sequence F, the number of $f_k = 1$ and $N_{f=1} = \sum_{k=i}^{k=j} f_k$ and the threshold $is\ R_f$, then

1. If $\frac{N_{f=1}}{M} < R_f$, it is determined that L is the background noise in the traffic sign detection candidate region.
2. If $\frac{N_{f=1}}{M} \ge R_f$, it is determined that the traffic sign detection candidate region is L as the traffic sign area.

If L is the traffic sign area, the traffic sign information area of the missing or lost frame can be backtracked.

The missing frame state value $(f = 0)$ in $F[f_i, f_{i+1}, \dots, f_j]$ is modified to $(f = 1)$, and its location and size are determined same time.

Similarly, the traffic sign candidate area L can be iteratively tracked in the time period after the time point t_j according to the continuous change in relationship (i.e., position offset and size change) of the traffic sign $t_i, \ldots, t_j (1 \leq i < j \leq n)$), the process is a recursive process.

The function ***Tracking*** (t_i, M) is used to trace the location and size of L in a continuous M frame after the start of the t_i moment. The recursion terminates the following three:

1. L position beyond the border.
2. L size is greater than the maximum size of traffic signs L_{max};
3. $M \leq 1$;

Recursive body:

Tracking (t_i, M) tracks L while checking whether it is a traffic sign. If the frame tracking results in the M frame are verified correctly, $i = i + M, M = \mathrm{M}/2$ will be followed; otherwise, the tracking will be stopped directly.

Recursive function body, Tracking (t_{start}, M) tracks the Traffic Sign estimated region and verify whether it is a Traffic Sign or not. If the verification results are true in more than half of M frames, then $t_{start} = t_{start} + \mathrm{M}, \mathrm{M} = \mathrm{M}/2$, and call Tracking (t_{start}, M). Otherwise, break iterative loop.

4. Experimental Data Analysis

The analysis of the data using the above algorithm and developed model for the "Traffic Sign Detection and Recognition has many dimensions. We worked on limiting the data sets in addition to finding a reliable and efficient detection and recognition system.

The experimental data is achieved by the driving recorder in different time periods and in different light conditions. The resolution of the video image is 1920 × 1080 and the frame rate is 30fps. Video contains morning, noon, afternoon, and other time periods including cloudy, sunny, rainy, foggy, and other weather conditions. This paper mainly evaluates the algorithm in terms of accuracy, robustness, and efficiency. The specific parameters of the running environment are shown in Table 1.

Table 1. Operating Environment Specific Parameters

Operating Environment	64 Bits Windows Ultimate
CPU	Intel(R) Core (TM) i5-3450
RAM	8GB
Runtime Environment	Visual Studio 2013
OPENCV Edition	Opencv3.0
Programming Lang.	C++

4.1. Robustness Testing

According to the different partitioned block size in the image segmentation compression algorithm, this paper tests the uninterrupted operation of video for more than 10 hours. The experiment results show that different sizes of partitioned blocks are set as 2, 4, 6, 8 and 16. There is no memory overflow, limited access or program interruption during the processing. In this paper, urban road traffic sign detection algorithm based on Time Space Relationship Model is robust and the program has high stability.

4.2. Accuracy Testing

Table 2. Experiment results at different time

Videos	Timing	Number	Accuracy
01	Morning	309	90.94%
02	Noon	285	90.88%
03	Afternoon	257	91.44%

Table 2. shows accuracy results of traffic sign detection at different time slots in a day in three different videos. Whereas Fig. 13 shows that this algorithm has better detection effect for complex road background, varying

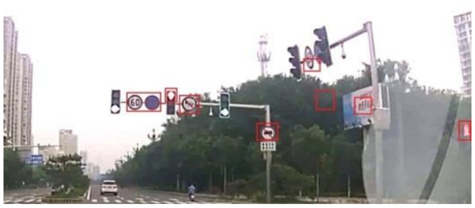
weather conditions when processing video data.

(a) Normal background

(b) The Dark Background

(c) Complex road background

Fig. 13. *Test results under various conditions*



(a) Before application

(b) After application

Fig. 14. *Result Before and After TSRM.*

Fig. 14 shows the comparison in between a video, before and after applying The Time Space Relationship Model, where TSRM eliminates the false positive candidate regions.

Through the processing of 3 hours of video, the test results before and after applying Time Space Relationship Model are shown in Table 3. From the test results, it can be seen that the accuracy of traffic sign detection is increased with TSRM nearly by 8% and the missed detection rate is reduced by nearly 7%.

Table 3. Result Comparison with TSRM

Experimental Results	**The Number of Signs**	
	Before TSRM	**After TSRM**
Actual Signs	309	309
Tested Signs	345	321
Correctly Detected	257	281
Missed Detection	52	28
Missing rate	16.83%	9.06%
Accuracy	83.17%	90.94%

Whereas Table 4 compares this algorithm with other literature algorithms. This paper not only outperforms literature [16] and literature [17] in accuracy, but also takes much less time to process high resolution images than other literature. Therefore, this algorithm meets the real-time detection requirements in mobile system.

Table 4. Comparison between proposed algorithm and other literature algorithms

Parameter	**Literature**		
	This paper	**[16]**	**[17]**
Accuracy rate	90.94%	86.8%	90.86%
Image size	1920 × 1080	640 × 480	1360 × 800
Processing time	25ms	200ms	780ms

4.3. Efficiency

The frame rate of the experimental video is 30fps, and the resolution of each image is 1920*1080. The average detection time of each image is about 25ms, that is, 40 frames per second can be processed to meet the real-time processing requirements. Therefore, the system is considerably efficient.

5. Traffic Sign Recognition Using SVM

The traffic sign detection and recognition were done by real-time capturing of the data and then analysing the obtained frames. The recognition analysis was done using the Support Vector Machine (SVM).

Table 5. Traffic Sign Recognition Sample Library

No.	Traffic Sign	Icon	Sample Numbers
01	No Stopping		252
02	Speed limit 40		228
03	No Horn		204
04	Watch for Pedestrians		232
05	Attention traffic lights		180
06	Turn right sign		196
07	Others	/	960

5.1. Traffic Sign Classification

According to the color and shape characteristics of traffic signs the candidate areas are labelled as prohibited signs (red), warning signs (yellow) and indicating signs (blue) in the color segmentation stage. Further classification is made according to the shape, and Fig. 15 is the process of classification and recognition of traffic signs:

In the red sign, the Hough circle detection is carried out in the candidate region image. If there is a circle, it is divided into the subclass 1; otherwise, it is judged as noise.

In the yellow warning sign, the Canny operator edge detection is carried out on the candidate region image, and the positive triangle detection method is adopted. If the region is triangle, it is divided into the subclass 2; otherwise, judged as noise & discarded.

In the blue indicator, the image of the candidate region is detected by Hough circle. If there is a circle, it is divided into subclass 3; otherwise, it is divided into the subclass 4.

5.2. Dataset Training & Recognition

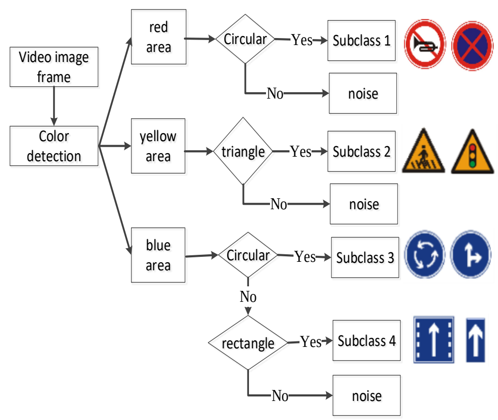


Fig. 15. *Traffic Sign Classification Process*

This paper uses SVM trainer in OPENCV computer vision library to implement the classification of traffic signs. The recognition framework process is as follows:

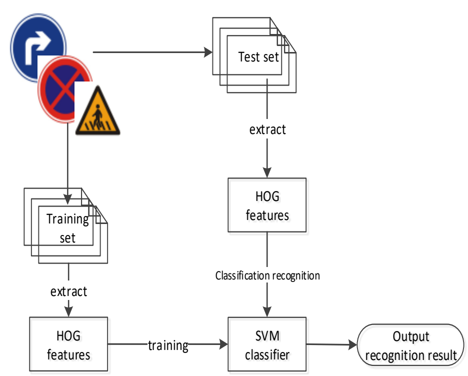


Fig. 16. *SVM Dataset Training & Recognition Process*

When the algorithm is implemented, the HOG feature of the traffic sign in the sample library is extracted first, and then the SVM classifier is used to train the sample to obtain the traffic sign classifier. When the traffic sign in the traffic video is detected, it is sent to the SVM classification according to the classification results output. Fig. 17 shows the traffic sign recognition result.

Fig. 17. *On-Road Traffic Sign Recognition*

Here in Fig. 17, we can see that speed sign is perfectly detected and then after using the model analysis, the recognition of the speed limit is recognized as 40.

Fig. 18. *Multiple traffic signs detection and recognition*

In Fig. 18 we observe four sign boards and system recognizes all traffic signs accurately.

Fig. 19. *Road Turning sign error (SVM)*

In Fig. 19, we observe that the vehicle is turning, and, in the process, it detects all the signs but fails to recognize the speed signal and gives a value of 80, instead of 60. This can be due to the angle at which the camera is reading the value. Several traffic signs with higher classification error rate can be seen, as shown in Table 6.

Table 6. Higher classification error rate

Sign type	Error rate
Crosswalk	7.22%
No-vehicle Lane	5.53%
No parking	2.24%
No entry	1.56%
Pedestrian Walk	1.54%

Table 6 shows that several traffic signs with higher classification error rate are caused by the smaller proportion of main color. When training SVM classifiers, most of the sample sets come from real-time urban road scenes, considering all the unfavourable factors such as weather, light conditions, and deformation. Even then the recognition effect is better. At the same time, SVM supports small sample training and has strong generalization ability and ensures the experiment results at higher accuracy.

Table 7. This paper and other literature comparison results

Study	System	Image size	Processing time (ms)
Reference [18]	3.33GHz Intel Core i5	640 × 480	50
Reference [19]	2.4 GHz Intel Core 2 with 4 GB RAM	1355 × 781	Detection: 400
Reference [20]	Intel Core i7-930 with 3 GB RAM	640 × 480	180
This paper	Intel Core i5 with 4 GB RAM	1920 × 1080	Detection: 25 Classification : 10

As shown in Table 7, comparing the average single-frame processing time of traffic sign recognition system with other literature processing time, we can see that the average processing time of single-frame algorithm is lower than dealing with larger resolution. That is to say, this traffic sign recognition system can meet the requirements of real-time processing.

6. Conclusion

Detection and recognition of road traffic sign is an important part of the Modern Intelligent Transportation Systems. Its effectiveness lies in warning the driver with any possible mishap on the road. Defined in this research work is an innovative and robust Time Space Relationship Model for the urban road traffic signs detection and recognition from a moving vehicle with high accuracy and efficiency. Color and shapes are used for the traffic signs detection in addition to support vector machine (SVM) for recognition. The research has contributed towards developing a framework which uses fast color segment algorithm to extract the traffic sign candidate regions, hence reducing the computational load.

Additionally, it also verifies the traffic sign candidate areas to decrease false positives and raise the accuracy by analyzing the variation in preceding video-images sequence while implementing the proposed Time Space Relationship Model.

The findings of the research reveal that the proportion of positive detection and recognition of road traffic sign is above 95.8%. Furthermore, the research framework achieved better accuracy, efficiency, and the robustness in real time.

7. Recommendation

Although the accuracy and real-time performance of the traffic sign recognition system in current study can meet the requirements, there are still areas for improvement. The Time Space Relationship Model can further be improved to decrease the false positive and high positive recognition can implement the multi-layer CNN architecture to achieve high accuracy. Furthermore, the study can be applied over the mobile system efficiently. In the future, technologies such as cloud computing and data mining can be used to analyses and excavate the massive data provided by the mobile terminal and contribute to the future intelligent transportation system.

AUTHOR CONTRIBUTION

Bhutto Jaseem Ahmed: Conceptualization, Methodology, Software, Data Curation, Writing - Original Draft, Writing - Review & Editing. **Qin Bo:** Conceptualization, Methodology, Resources, Supervision, Project administration, Funding acquisition**. Qu Zabo:** Software, Validation**,** Formal analysis**. Zhai Xiaowei:** Software, Investigation Visualization. **Abdullah Maitlo:** Writing - Review & Editing.

DATA AVAILABILTY STATEMENT

The datasets generated during and/or analyzed during the current study are not publicly available since the datasets are sole property of CGIV Lab, Computer Science and Technology department, Ocean University of China, China. However, these datasets are available from the corresponding author on reasonable request and can be shared if permission is granted from Lab.

CONFLICT OF INTEREST

The Authors of this paper declare no conflict of interest.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or non-profit sectors.

ACKNOWLEDGMENT

The Support of the “Computer Graphics, Image-Processing and Vision (CGIV) Lab” established in Department of Computer Science and Technology, Ocean University of China is hereby acknowledged. We would also like to show our gratitude to the anonymous reviewers for their so-called insights. We are also immensely grateful to Ms. Humera Wagan (Communication Security Officer) for her critical comments on an earlier version of the manuscript that greatly improved the manuscript.

REFERENCES

[1] Fleyeh, H., 2006. Shadow and highlight invariant colour segmentation algorithm for traffic signs. In: Cybernetics and Intelligent Systems, 2006 IEEE Conference on, pp. 1–7.

[2] Gomez-Moreno, H., Maldonado-Bascon, S., Gil-Jimenez, P. and Lafuente-Arroyo, S., 2010. Goal evaluation of segmentation algorithms for traffic sign recognition. IEEE Transactions on Intelligent Transportation Systems 11(4), pp. 917 – 930.

[3] Shadeed, W.G.; Abu-Al-Nadi, D.I.; Mismar, M.J. Road traffic sign detection in color images. In Proceedings of the 2003 10th IEEE International Conference on Electronics, Circuits and Systems (ICECS2003), Sharjah, UAE, 14–17 December 2003; pp. 890–893.

[4] Li, H., Sun, F., Liu, L. and Wang, L., 2015. A novel traffic sign detection method via color segmentation and robust shape matching. Neurocomputing 169, pp. 77–88.

[5] Barrile, V., Meduri, G. M. and Cuzzocrea, D., Automatic recognition of road signs by hough transform: Road-GIS. Journal of Earth Science & Engineering, Vol. 2, 2012, pp. 42-50.

[6] Landesa-Vazquez, I., Parada-Loira, F. and Alba-Castro, J., 2010.Fast real-time multiclass traffic sign detection based on novel shape and texture descriptors. In: Conference Record – IEEE Conference on Intelligent Transportation Systems, pp. 1388–1395.

[7] Liu, C., Chang, F. and Chen, Z., 2014. Rapid multiclass traffic sign detection in high-resolution images. IEEE Transactions on Intelligent Transportation Systems 15(6), pp. 2394–2403.

[8] Heng, L., Lee, G. H., Fraundorfer, F. and Pollefeys, M., 2011. Real-time photo-realistic 3d mapping for micro aerial vehicles. In: IEEE/RSJ International Conference on Intelligent Robots & Systems IEEE/RSJ International Conference on Intelligent Robots & Systems, pp. 4012–4019.

[9] Crandall, D., Owens, A., Snavely, N. and Huttenlocher, D., 2011. Discrete-continuous optimization for large-scale structure from motion. In: IEEE Conference on Computer Vision & Pattern Recognition, pp. 3001–3008.

[10] Golparvar-Fard, M., Balali, V. and Garza, J. M. D. L., Segmentation and recognition of highway assets using image-based 3d point clouds and semantic texton forests. Journal of Computing in Civil Engineering, 2012, 29.

[11] Yang M., Gu X., Lu H., Wang C. and Ye L., 2015. Panorama-Based Multilane Recognition for Advanced Navigation Map Generation. Mathematical Problems in Engineering 2015, pp. 1–14.

[12] Riveiro, B., Diaz-Vilarino L., Conde-Carnero, B. and Soilan, M., 2015. Automatic Segmentation and Shape-Based Classification Of Retro-Reflective Traffic Signs from Mobile Lidar Data. IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing pp. 1–9.

[13] Yu, Y., Li, J., Wen, C., Guan, H., Luo, H. and Wang, C., 2016. Bag-Of-Visual-Phrases and Hierarchical Deep Models for Traffic Sign Detection and Recognition in Mobile Laser Scanning Data. ISPRS Journal of Photogrammetry & Remote Sensing 113, pp. 106–123.

[14] Ashish-Pradhan. Network Traffic Classification Using Support Vector Machine. International Journal of Computer Applications · October 2011.

[15] Traffic Sign Detection and Positioning from Google Street View Streamlines. Victor J. D. Tsai. Asprs 2015 Annual Conference Tampa, Florida May 4-8, 2015.

[16] Radu Timofte, Victor Adrian Prisacariu, Luc Van Gool, and Ian Reid. Combining Traffic Sign Detection With 3D Tracking Towards Better Driver Assistance. World Scientific Review Volume – 9. March 23, 2011.

[17] J. Greenhalgh, M. Mirmehdi. Real-Time Detection and Recognition of Road Traffic Signs. Intelligent Transportation Systems IEEE Transactions on, 2012, 13(4):1498-1506.

[18] 汤凯, 李实英, 刘娟,等. 基于多特征协同的交通标志检测[J]. 计算机工程, 2015, 41(3):211-217

[19] Houben S, A Single Target Voting Scheme for Traffic Sign Detection. In: Intelligent Vehicles Symposium. IEEE, 2011:124-129.

[20] Gu Y, Yendo T, Tehrani M P, Fujii T, Tanimoto M. Traffic Sign Detection in Dual-Focal Active Camera System. In: IEEE intelligent vehicles symposium Germany, 2011, 1054–1059