

Novel Graph Based Ranking Method for the Detection of Traffic Sign

S. Haseena

Assistant Professor

Department of Information Technology

Mepco Schlenk Engineering College, Sivakasi, Tami Nadu

Corresponding Author's Email: haseena@mepcoeng.ac.in

Abstract

The best part of accessible traffic sign detection system make use of color or shape information, but the process stays limited in regard to identify and segmenting traffic signs from a complex background . In this paper, we intend a novel graph based traffic sign detection path that contains a saliency measure stage, multi-threshold segmentation stage and a graph based ranking stage. Since the graph based ranking algorithm with specific color and saliency associates the information of color, saliency, structural and dependent relationship of nodes , it is more particular and robust than the other systems in terms of use of various illumination state ,shape rotations and scale modify from traffic sign images . Additionally, the proposed multi-threshold segmentation algorithm target of all nodes with a nonzero ranking score, which can efficiently solve problems such as various lighting conditions, complex background, occlusion and so on. The results for three public traffic sign position demonstrate that out proposed approach guide the better performance than the existing state of the art technique. Additionally, the results are suitable even for images hold traffic signs that have been rotated or experienced occlusion with the images that were photographed under dissimilar weather and illumination state.

Keywords: *Graph based image segmentation, Graph analysis, traffic sign detection, support vector machine*

INTRODUCTION

A novel method is intended for the Traffic Signal Recognition (TSR) with the Principle Component Analysis (PCA) and the Multi-Layer Perceptron (MLPs) network[1]. In morphological classification method, the candidate signs are individually detected from two chrome components of the YCbCr space and then classified into three shape classes namely circle, square, and triangle based on computing the rotated version correlations. The PCA-based features of these signal objects will be used for the MLPs as the training system linked to previously determined class. This approach not only reduces the time but also improves the performance in the recognition process. In simulation, the planned method is predictable with over 500 value images and its precision rate is up to 96%.

A novel graph based traffic signal detection approach that contains a saliency measure point[2], a graph-based ranking stage, and a multi-threshold segmentation period. Since the graph-based ranking algorithm with particular color and saliency merges the information of color, saliency, spatial, and appropriate connection of nodes, it is more discriminative and strong than the other systems in terms of management of

various illumination conditions, shape rotations, and scale changes from traffic signal images. Furthermore, the proposed multi-threshold segmentation algorithm focuses on all the nodes with a nonzero ranking score, which can efficiently resolve difficulties such as complex background, occlusion, various illumination states, and so on. The results for three public traffic signal sets explain that our proposed approach leads to better performance than the current state-of-the-art process. Besides, the results are suitable even for images holding traffic signals that have been revolved or undergone occlusion, as well as for images that were snapped under different weather and illumination state.

A road-signal detection and identification system based on support vector machines (SVMs) is discussed in [3]. In automatic traffic-signal protection and in an image driver assistance system, road-signal detection and identification are two of the most important roles. Our system is capable to identify and recognize circular, rectangular, triangular, and octagonal signals and, hence, covers all existing Spanish traffic-sign shapes. Road signals supply driver's significant information and help them to drive more securely and more easily by guiding and notice them and thus

regulating their actions. The proposed recognition system is based on the generalization properties of SVMs. The system contains three stages: 1) segmentation dealing with the color of the pixel; 2) traffic-signal detection by shape classification using linear SVMs; and 3) content recognition based on Gaussian-kernel SVMs. Because of the used segmentation stage by red, blue, yellow, white, or grouping of these colors, all traffic signals can be identified, and some of them can be noticed by several colors. Results show a high success rate and a very low amount of false positives in the final recognition phase. From these results, we can terminate that the proposed algorithm is invariant to translation, rotation, scale, and, in many situations, even to incomplete occlusions.

A state-of-the-art traffic sign recognition system[4] that is capable to recognize and categorize 43 different German traffic signals. To preserve a high performance and scalability of the system we use a two-stage approach that divides the detection from the classification step. We use a fast shape detection method based on multi block local binary patterns that has exposed to give good results for a face detection application. Color segmentation is also used alongside the shape detector.

This improves the affine invariance properties and overall detection rate of the system. For the classification, we rely on HOG-Features and nonlinear support vector machines. Our classifier attains a score of 96.93% on the German Traffic Signal recognition Benchmark that can be measured as a top scoring result. While this benchmark is a pure classification benchmark that employs bounding boxes with centered signals.

We also estimated the detection capabilities of our system on 108 traffic images given by a street inspection company. Our system identified and classified 97% of the traffic signals in this data set correctly while the false positive rate was very low.

GRAPH-BASED RANKING AND SEGMENTATION ALGORITHM FOR TRAFFIC SIGN DETECTION

Super pixels are proficient by the simple linear iterative clustering (SLIC) algorithm that clusters pixels in the shared five-dimensional color and image plane space to accomplished, generate compact, almost uniform super pixels. The flow of our proposed traffic signal detection system is represented in fig 1. The examples of the super pixels are generated and demonstrated in Fig. 2(a)–(c). To

identify small traffic signals, the system must assure that the color border of the traffic signals is divided into independent super pixels. Therefore, in this paper we choose 4000 super pixels.

Combining Color, Saliency, and Contextual Relationship of Nodes

Input:

C = complete affinity matrix

W = affinity matrix is defined by Eq.(1)

S = saliency map is defined by Eq. (3)

Output: complete affinity matrix which combines the information of saliency and contextual relationship of nodes.

Step 1: All the nodes belonging to traffic sign regions have high saliency values, the relevance of the I node and the nodes having low saliency values should be removed as follows:

if $S(i) = 0 \quad i \in \{1, \dots, N\}$,

then $C(j, i) = 0, j = \{1, \dots, N\}$,

otherwise $C(i, j) = C(i, j)$.

Step 2: the relevance of the i-node and unconnected nodes should be ignored as follows:

if $W\{i, k\} = 0, i \in \{1, \dots, N\}, k \in \{1, \dots, N\}$

then $C(i, k) = 0$,

otherwise $C(i, k) = C(i, j)$

A. Graph Design

We create a graph $G = (V, E)$, as shown in Figs. 3(b), in which V is a group of nodes and E is a group of undirected edges. In this paper, every node is a superpixel created by the SLIC algorithm. To develop the spatial connection, we implemented a k-regular graph that is a graph with vertices of degree k. By expanding the scope of node relationship with the similar degree of k, we successively make use of a local evenness signal. Each node is not only connected to its adjacent nodes, but also linked to the nodes sharing common boundaries with these adjacent nodes (see Fig. 4). The weight w_{ij} join each pair of nodes i and j, which is defined by the following

$$w_{ij} = \exp\left(-\frac{\|\bar{p}_i - \bar{p}_j\|}{2\sigma^2}\right) \quad (1)$$

Where $\bar{p}_i$ represents the mean color values of the inner pixels of nodes (super pixels) i in the normalized version of RGB color space, correspondingly, and σ is stable that organize the power of the weight. The edges E are weighted by an similarity matrix $W = [w_{ij}]n \times n$. With the limitation on the edges, it is clear that the constructed

graph is thinly connected, that is most part of the affinity matrix W are zero.

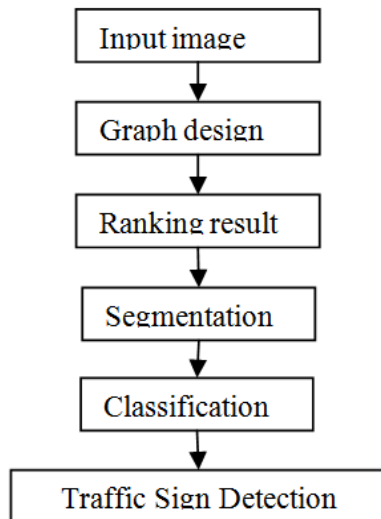


Figure 1: Flow Diagram of proposed system

B. Visual Saliency Measure for Each Node

In Fig 2, each node is a super pixel created by the SLIC algorithm. V is a position of nodes and E is a position of undirected edges. The neighbouring nodes applied to the background are likely to split similarity appearance, but the nodes applied to the traffic signal section have high saliency values. Particularly, for any node i , the saliency is

$$Saliency(i) = \sum_{p=1}^N v_{ip} / M \quad (2)$$

Where v_{ip} is a weight joining both pair of nodes i and p , which can be acquired in (1), and M is the number of the

neighbouring nodes of node i . The top TH1 nodes with the major salient score in an image are considered to be salient nodes. The patterns of salient nodes selected and approximately all the nodes belonging to traffic signal section have high salient importance which is calculated as in equ(3). The TH1 here is put to 25% by constructing the highest F -measure.

$$S(i) = \begin{cases} 1 & \text{if } Saliency(i) \in \text{Top TH1} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

C. Ranking Algorithm with Specified Colors and Saliency

In [5], presented a saliency detection algorithm (SDA) on the beginning of graph-based manifold ranking [6], [7], [8]. An image was characterized as a close-loop graph with superpixels as nodes. Via graph-based manifold ranking, accordingly ranked these nodes on the source of their relationship to the background and foreground signal. They performed saliency detection in a two-stage method. First, they applied the nodes on the image boundary as background seeds, then raised four saliency maps using boundary priors, and integrated these for the final map. Consequently, they binary segmented (i.e., salient foreground and background) the

saliency map of the first stage, using an adaptive threshold, which facilitated the selection of the nodes of the foreground salient object as queries.

Our objective is to study a ranking function, which describes the consequence between the nodes of the graph and group of the traffic signal colors. The core plan of manifold position is to rank the nodes with respect to the intrinsic arrangement collectively. By taking the significance between the nodes of the graph and collection of the traffic signal colors, manifold ranking allocate each node a virtual ranking score, as a replacement of a fixed pairwise relationship as traditional ways. In conflict with our aim, we characterized a traffic signal detection system as a manifold ranking difficulty. The proposed traffic signal detection algorithm with manifold ranking requires seeds from several classes, which are initialized with the vary of colors of the traffic signal (red, blue, and yellow).

Given a vector $V = \{v_1, \dots, v_n\} \in m \cdot n$, every element on vector V is a node, and the nodes must be ranked dealing with their importance to the objective queries. Let $F: V \rightarrow n$ indicate a ranking task that allot a ranking score, F_i to each node v_i , and F can be examined as a vector $F =$

$[F_1, \dots, F_n]^T \in \mathbb{R}^n$. Where T is the symbol of transpose and $\mathbb{R}^n$ signifies a group of $n \times 1$ matrices with nonnegative entries. An objective query vector $Y = [Y_1, \dots, Y_n]^T$ means a vector to explain the relationship between the nodes and specified colors. Based on the properties of traffic signals, the nodes belonging to the traffic signal section should not adjust extensively between nearby nodes, nor should they vary significantly from the ranges of the traffic signal colors. The optimal rankings are calculated by resolve the subsequent optimization problem. The cost function connected with F is defined to be

$$\theta(F) = \arg \min_F \frac{1}{2} \left(\sum_{i,j=1}^n w_{ij} \left\| \frac{E_i}{\sqrt{D_{ii}}} - \frac{E_j}{\sqrt{D_{jj}}} \right\|^2 + \mu \sum_{i=1}^n \|E_i - Y_i\|^2 \right) \quad (4)$$

Where $\mu > 0$ is the regularization parameter, D is the degree matrix with the off diagonal elements,

$D_{ii} = \sum_j w_{ij}$, and w_{ij} is. Then the optimization function is

$$F^* = (D - \alpha W)^{-1} Y \quad (5)$$

Where the parameter μ controls the equilibrium of the smoothness constraint

and the fitting constraint a good ranking function should not change too greatly linking nearby nodes nor should it differ too greatly from the objective query assignment. The lowest solution is calculated by setting the derivative of the beyond function to be zero. By ranking the nodes on the constructed graph, we can regard the inverse matrix as a complete affinity matrix. This is a nonzero relevance value that exists between any pair of nodes on the graph, and represents the relationships of spatial distances and similarities between any pair of nodes. The relevance between nodes increases when their spatial distance is decreased. The ranking score $F^*(i)$ of the i th node is the inner product of the i th row of Y . Because Y is a binary vector, $F^*(i)$ can also be viewed as the sum of the relevance's of the i th node to the objective query. In this paper, we propose an algorithm to combine the information of saliency and the contextual relationship of nodes as presented in Table I, and gain a new absolute affinity matrix C , which can illustrate the information of saliency and spatial, background relationship of nodes. We set α to 0.9.

The threshold α here is set based on experience. It is worth noting that this seemingly insignificant process in fact has

significant effect on the final results. If we compute the ranking map without setting the nodes having low saliency values to 0, the ranking values of the nodes belonging to large area sections with specified colors turn abnormally large, so as to severely decline the parts of the others to the ranking score.

D. Traffic sign candidate regions segmentation:

Based on the ranking algorithm, the method gives a ranking score for each node, which shows how likely it is to be a part of traffic signal. To separate the traffic signal states from the results of the ranking algorithm, we suggest a multi-threshold Segmentation algorithm. Every image of ranking result is binarized at a number of different threshold levels, and the connected components at each level are found. Fig. 3 explains the different threshold levels for an example image with the connected parts colored. Each connected component can be illustrated as L_{zi} , which is the i th connected component at level z . Here, $i \in [1, 2, \dots, N_z]$ and $t \in [1, 2, \dots, Z]$.

To enlarge the speed, we threshold only at an appropriate range of values rather than at every possible value, the thresholds are set to 0.6, 0.4, 0.2, and 0.01. Furthermore,

were move the segments with areas that are either too large or small, and cut some segments whose heights are twice as longer as the width. The segmentation results are illustrated in Figs. 2(d) and 8. The threshold TH2 here is positioned to 1.1 by creating the highest F -measure.

E. Traffic Sign Classification Based on SVMs:

We apply SVM multiclass classification with linear SVM and utilize the library Linear in our system. The classification stage input is a vector of the HOG descriptor, planned for pedestrian detection. On the starting point of the gradients of the images, we estimate the different weighted and normalized histograms, overlapping cells with the size of 16×16 pixels, a block size of 4×4 cells, and an direction resolution of 8.

To categorize the decision region, all characterize vectors of a specific class are collected together adjacent to all vectors consequent to the remains of the classes according to the one-versus-all classification algorithm. SVM multiclass classification builds SVM models. The i th SVM is qualified with all the examples in the i th class with positive labels, and all other examples with negative labels. In this paper, the cost of a regularization parameter C is set to 1.2 by generating the highest cross-correlation precision.



Fig 2: Input image



Fig 3: Ranking with specified colors



Fig 4: Segmentation Result

III. EXPERIMENT RESULT

To estimate the effectiveness of the proposed traffic signal detection approach, we carried out a series of comparative experiments using three public traffic sign datasets. The experiments included two components, namely, traffic sign detection and classification. We should note that the main role of this paper is devoted to the traffic sign detection stage. Thus, we have supply complete experimental results involving to this stage.

Table 1 shows the comparison of our algorithm with different parameters.

Parameter	Value
α	0.8
Th1	24%
Th2	1.0

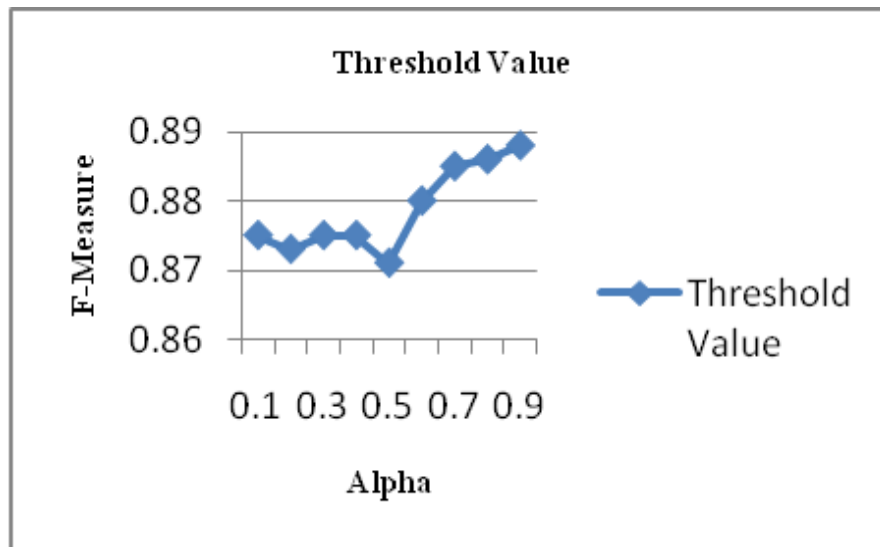


Fig 5: F-measure rates by varying parameters α

A. DATASETS:

1) Spanish Traffic Sign Set:

Several sequences on diverse routes and under different lighting states were captured. Every series included thousands of images. With the aim of analysing the most problematic situations, we use 313 images containing 466 color traffic signs whose size were larger than 30×30 pixels and the traffic signs may be sorted into 19 classes.

Eighty-four training images consisted of 191 traffic signs for training. The images presented different detection and recognition problems, such as low illumination, rainy conditions, an array of signs, similar background color, and occlusions. Examples of the Spanish traffic signal position.

2) GTSDDB Dataset:

The German traffic signal detection benchmark (GTSDDB) dataset have 900 images of 43 traffic signal category divided into 600 training images and 300 evaluation images Three hundred images include 296 color traffic signals whose sizes were superior to 30×30 pixels. All images in the dataset contains zero to six traffic signals, and they come out from every side, as well as under every lighting state.

CONCLUSION

In this paper, we explained a novel graph-based traffic signal detection approach, which contains a saliency measure phase, a graph-based ranking stage, and a multi

threshold segmentation period. We presented a graph with superpixels as nodes for an image, and gave the nodes ranking scores, dealing with their spatial structures, saliency, contextual relationship of nodes and similarities with the particular colors. We could then separate the traffic signal candidate zone with the specified colors from a complex background, on the basis of the multi threshold segmentation algorithm. To confirm the effectiveness of the detection module, we checked three traffic signal datasets, that is, the Spanish, GTSDb, and Swedish datasets. The images were confined under different conditions of geometric.

REFERENCES

- 1) HaiNguyen Thanh, "Morphological Classification for Traffic Sign Recognition", Electrical and Electronic Engineering 2014, 4(2): 36-44 , DOI: 10.5923/j.eee.20140402.03.
- 2) Xue Yuan, Member, IEEE, JiaqiGuo, XiaoliHao, and Houjin Chen, "Traffic Sign Detection via Graph-Based Ranking and Segmentation Algorithms", IEEE transactions on systems, man, and cybernetics: systems, vol. 45, no. 12, December 2015.
- 3) S. Maldonado-Bascón, J. Acevedo-Rodríguez, S. Lafuente-Arroyo, A. Fernndez-Caballero, and F. López-Ferreras, "An optimization on pictogram identification for the road-sign recognition task using SVMs," Comput. Vis. Image Understand., vol. 114, no. 3, pp. 373–383, 2010.
- 4) Kedkarn Chaiyakhan*, Anusara Hirunyawanakul, Ratiporn Chanklan, Kittisak Kerdprasop, Nittaya Kerdprasop, "Traffic Sign Classification using Support Vector Machineand Image Segmentation", Proceedings of the 3rd International Conference on Industrial Application Engineering 2015 © 2015 The Institute of Industrial Applications Engineers, Japan.
- 5) C. Yang, L. Zhang, H. Lu, X. Ruan, and M. H. Yang, "Saliency detection via graph-based manifold ranking," in Proc. CVPR, Portland, OR, USA, 2013, pp. 3166–3173.

- 6) D. Zhou, J. Weston, A. Gretton, O. Bousquet, and B. Scholkopf, "Ranking on data manifolds," in Proc. NIPS, 2004, pp. 169–176.
- 7) D. Zhou, O. Bousquet, T. N. Lal, J. Weston, and B. Scholkopf, "Learning with local and global consistency," in Proc. NIPS, 2003, pp. 321–328.
- 8) C. V. Gustavo, V. B. Tatyana, and D. Zhou, "Semi-supervised graphbasedhyperspectral image classification," IEEE Trans. Geosci. RemoteSens., vol. 45, no. 10, pp. 3044–3045, Oct. 2007.
- 9) R. Achanta et al., "SLIC superpixels compared to state-of-the-art superpixel methods," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 11, pp. 2274–2282, Nov. 2012.
- 10) M. S. Prieto and A. R. Allen, "Using self-organising maps in the detection and recognition.
- 11) S. Xu, "Robust traffic sign shape recognition using geometric matching," IET Intell. Transp. Syst., vol. 3, no. 1, pp. 10–18, 2009.
- 12) X. Yuan, X. L. Hao, H. J. Chen, and X. Y. Wei, "Robust traffic sign recognition based on color global and local oriented edge magnitude patterns," IEEE Trans. Intell. Transp. Syst., vol. 15, no. 4, pp. 1466–1477, Aug. 2014.
- 13) F. Zaklouta and B. Stanculescu, "Warning traffic sign recognition using a HOG-based K-d tree," in Proc. Intell. Veh. Symp. (IV), Baden-Baden, Germany, 2011, pp. 1019–1024.
- 14) J. Greenhalgh and M. Mirmehdi, "Real-Time detection and recognition of road traffic signs," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 4, pp. 1498–1506, Dec. 2012.
- 15) Z. Li, C. Dong, L. Zheng, and L. Liu, "Traffic signs detection based on haar-like features and adaboost classifier," in Proc. ICTIS, Wuhan, China, 2013, pp. 1128–1135.
- 16) Vishal R. Deshmukh, G. K. Patnaik, M. E. Patil, "Real-Time

Traffic Sign Recognition System
based on Colour Image
Segmentation,” International
Journal of Computer Applications
(0975 – 8887) Volume 83 – No3,
December 2013.

- 17) K. Lu, Z. M. Ding, and S. Ge,
“Sparse-representation-based graph
embedding for traffic sign
recognition,” IEEE Trans. Intell.
Transp. Syst., vol. 13, no. 4, pp.
1515–1524, Dec. 2012.
- 18) J. Stallkamp, M. Schlipsing, J.
Salmen, and C. Igel, “Man vs.
computer: Benchmarking machine
learning algorithms for traffic sign
recognition,” Neural Netw., vol.
32, no. 8, pp. 323–332, 2011.