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TRAFFIC SIGN DETECTION BASED ON SIMPLE XOR AND DISCRIMINATIVE FEATURES

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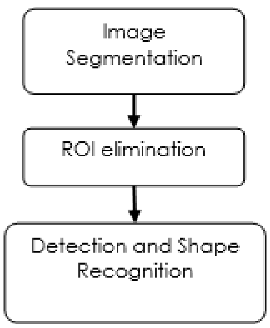
Graphical abstract



Abstract

Traffic Sign Detection (TSD) is an important application in computer vision. It plays a crucial role in driver assistance systems, and provides drivers with safety and precaution information. In this paper, in addition to detecting Traffic Signs (TSs), the proposed technique also recognizes the shape of the TS. The proposed technique consist of two stages. The first stage is an image segmentation technique that is based on Learning Vector Quantization (LVQ), which divides the image into six different color regions. The second stage is based on discriminative features (area, color, and aspect ratio) and the exclusive OR logical operator (XOR). The output is the location and shape of the TS. The proposed technique is applied on the German Traffic Sign Detection Benchmark (GTSDB), and achieves overall detection and shape matching of around 97% and 100% respectively. The testing speed is around 0.8 seconds per image on a mainstream PC, and the technique is coded using the Matlab toolbox.

Keywords: Color spaces; Image analysis; image segmentation; Traffic Sign Detection and Recognition (TSDR); exclusive OR logical operator (XOR); Learning Vector Quantization (LVQ); German Traffic Sign Detection Benchmark (GTSDB); Artificial Neural Networks (ANN).

1.0 INTRODUCTION

Traffic Sign Detection (TSD) is a part of Traffic Sign Detection and Recognition systems (TSDRs), which is among the on-road applications in computer vision [1].

Similar to other computer vision applications, a TSDR has several problems, including lighting conditions, motion blur, vehicle speed, signs within the same category that look similar to each other, weather affecting the visibility of signs, and signs that may be bent and not perpendicular to the vision system. Objects in urban or open roads may also look like traffic signs. Ever since the first paper appeared in Japan in 1984, the TSDR system has been an important issue in the computer vision research area [2].

A Traffic Sign (TS) must follow a specific design regulation in terms of shape, color, border color, background color, and pictogram (TS information) color. Thus, the detection of a TS is based on color, shape or a combination of both. In [3], the authors proposed a relative color method which was used to extract red bitmaps found in prohibitory and danger signs. Then they used a histogram of Oriented Gradient (HOG) features and a support vector machines (SVM) model to accurately detect the TS. On the other hand, using shape information, the authors in [4] used an edge segment detector to detect any circular objects (prohibitory TS) using gradient extrema points and the angle between two consecutive short lines. Other systems that are based on color or shape matching can be found in [5-7].

Due to the problems previously mentioned, detection systems that are based on only one type of information may not provide satisfactory results. For example, the color may change with time or erosion. Moreover, in urban or cluttered scenes, ordinary objects may have the shape of a TS. Therefore, [8-13] proposed a detection technique based on the use of color, shape and machine learning to detect the TS. This technique makes the detection more robust, accurate and reliable.

As a result of the complexity found in any scene environment, image segmentation plays an important role in detecting the TS. Some image segmentation techniques use a fixed threshold and searches for a pixel value that is related only to Red [3]. In [14], the authors proposed a segmentation process based on the colors that can be found in any TS, and the image is segmented based on five colors: red, yellow, orange, white and bright yellow. They adapt the HSV color space. But if the TS color for any reason is not within this threshold, this technique cannot accurately segment the image, hence leads to a missed TS detection. Others adapt a relationship between color bands [5, 8, 15]

Recently, TS image segmentation is based on ANN. In [8], a segmentation is performed using a Pre-trained SVM network based on the RGB color system to highlight the ones that are related to TSs. This was presented in the German Traffic Sign Detection Benchmark (GTSDB) competition found in [16]. The problem in this method is that it is time consuming in collecting the training data from TS scenes, and the color space used is not robust against changes in illumination.

Others segment the TS scene based on the standard shapes of a TS such as circle, triangle, octagon, square, rhombus and so on. The techniques presented in [4, 7, 17] are robust to illumination changes, but not to objects or shapes are similar to TS shapes.

In this paper, a TS detection technique is proposed based on the color and shape properties of TSs. In particular, it uses an image segmentation technique based on learning vector quantization (LVQ) and discriminative features such as area, number of pixels and aspect ratio. The final stage is to refine the Region of Interests (ROIs) to remove objects that are not TSs. This is done by the bitwise logical XOR operator, and at the same time, shape classification is performed. The output from the shape classification process is one from five classes that represent the five shapes found in the GTSDB [16]. The overall performance of the proposed technique outstands the performances obtained in the competition. In the competition, the best performance method was selected according to each TS category (prohibitory, danger and mandatory). In addition, the performance of the proposed technique is tested on all of the TS categories.

2.0 TRAFFIC SIGN DETECTION SYSTEM

The proposed detection system framework (0) consists of three main consecutive processes, namely, image segmentation, ROI elimination, and detection and shape recognition. The details of each of these processes are described in the following sections.

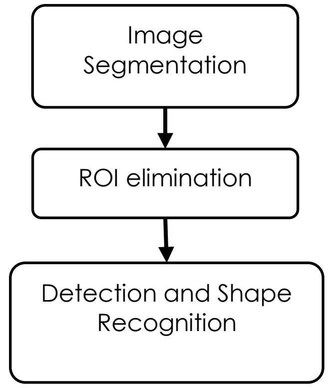


Figure1 Proposed detection system framework

2.1 Image Segmentation

To overcome the complexity found at traffic scenes, as in 0, a segmentation technique which was used in [18] is adopted in this work. The segmentation technique is based on the HSV color space, which is robust to illumination variation. HSV codes the color information in only one band, unlike the RGB color scheme. The segmentation technique skips the process of collecting the training data, as it depends on randomly generated data which represent six colors (white, black, yellow, blue, red, and green).

Figure 2 Random sample scene found in GTSDB

An LVQ approach is applied to assure the speed of the proposed segmentation technique. LVQ uses a supervised distance-based neural network classifier that requires a training dataset, where each dataset has n-prototypes. The prototypes, after the training phase, represent the different color classes. In the testing phase, the Euclidean distance is calculated between the given input and the trained prototypes. The smallest distance gives the class output for this specific input [18, 19].

The segmentation technique is composed from two separate phases: training and testing [20].

1. Training phase:

In which the system studies the input data and learns it for further usage, which consists of four stages:

a. Randomly create HSV data that represents different color values.
b. Create *N* samples for each class (Color).
c. For each class create *m*-prototypes.
d. Train the prototypes using the LVQ training algorithm.

2. Testing phase:

In this phase the system decides the class of the input data (HSV data) depending on what the system has learned in the training phase. It consists of three stages:

a. Feed the system with the values of sample HSV data taken from the TS scene.
b. Calculate the distance between the input and the trained *m*-prototypes.
c. Decide the class (Color) depending on the smallest calculated distance.

The segmentation process produces six different images, each of which represents one color, as in 0. From these images, the focus will be only on red and blue bands, which are the only colors associated with TSs found in GTSDB.

(a) Germany TS scene

(b) Germany TS segmentation

Figure 3 TS segmentation for TS scene found in GTSDB

2.2 Region of Interest (Roi) Elimination

The elimination process is based on discriminative features which decide whether a specific ROI is related to a possible TS. The flowchart in 0depicts the three stages of this process, which is described in the following sections.

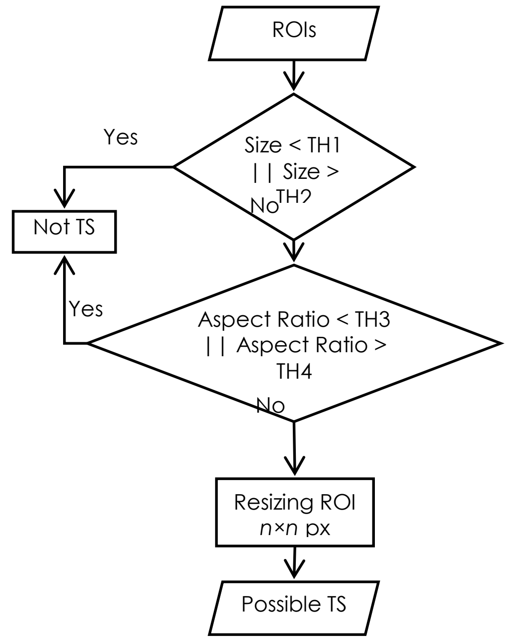


Figure 4 Elimination process flowchart

1. ROI size

The size of any ROI gives sufficient information on whether the ROI a proper TS. A certain ROI is eliminated if its size is too small or large. In other words, if the ROI size is within a specific range, it is a proper TS; otherwise, it is not.

2. ROI aspect ratio:

The aspect ratio is defined as the ration between the width and height of any object. From the properties of TS shapes, normally the width and height are almost equal to each other. A threshold is applied to each ROI; if the ROI aspect ratio is within that range, then it is considered as a possible TS; otherwise the ROI is eliminated.

3. Resizing ROI:

The final step is to resize the remaining ROIs to become equal in size. This process aims to align any kind of rotation around the Y and Z axes. In addition, ROI resizing provides a homogenous region and makes the matching between the dataset and the given ROI easier.

2.3 Detection And Shape Recognition

The remaining ROI still requires the refinement process presented in 0. During the first step, each ROI is converted to black and white, and is then labeled with its original color. For example, if the ROI is red, the red pixels become white, and this ROI is labeled as a red ROI.

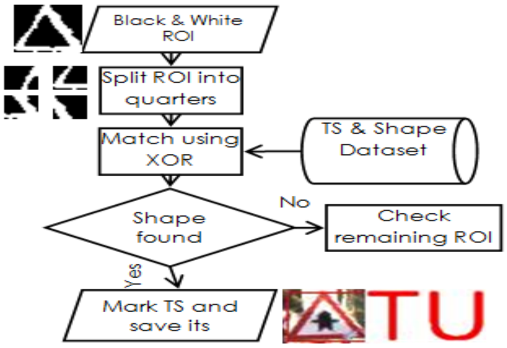


Figure 5 Detection and Shape Recognition flowchart

Subsequently, each ROI is split into quarters to produce four different regions beside the whole ROI. The matching process is performed by comparing each one from the five samples (whole ROI and four regions) with the TS and shape dataset. This process is performed using a bitwise logical operator (XOR). The ROI is considered to be a TS if either of two conditions is satisfied. The first condition is whether there is a match between the whole ROI and the dataset. The second is whether at least three regions are found in the dataset, which allows the detection of a partially occluded TS.Finally, if an ROI is considered to be a TS, a bounding box is placed around it, stating its border color and shape. This process is carried out when all of the existing ROIs are checked and classified as TSs.

3.0 RESULTS AND DISCUSSION

The GTSDB dataset [16] was used to evaluate the technique proposed in this paper. This widely used dataset facilitates the comparison of the results obtained in this work with others. The dataset contains two kind of images, one with only TSs, and the other a whole road scene, as depicted in 0.

Figure 6 TS samples as found in GTSDB, the first three rows repersent only a TS and the last row is a road scence

The shape TS dataset is created from the first type of GTSDB by applying an image segmentation technique which was proposed in [20] to separate the border of the TS from its background and pictogram. The output from this process is illustrated in **Error! Reference source not found.**.

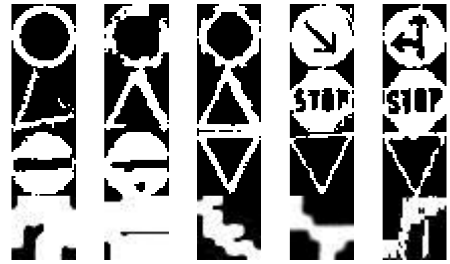


Figure 7 TS shape dataset samples; each is 32x32 pixels; the rows from one to three represent a TS shape, while the last row represents a non-TS sign shape

In the GTSDB, a total of 900 road scenes were found, 600 images for training purposes, and 300 images for testing. A comparison between the top ten results and the proposed technique is presented in 00and 0 for prohibitory, danger and mandatory TS, respectively, according to the precision-recall curves. Precision is the fraction of retrieved TSs that are relevant, while recall is the fraction of relevant TSs that are retrieved.

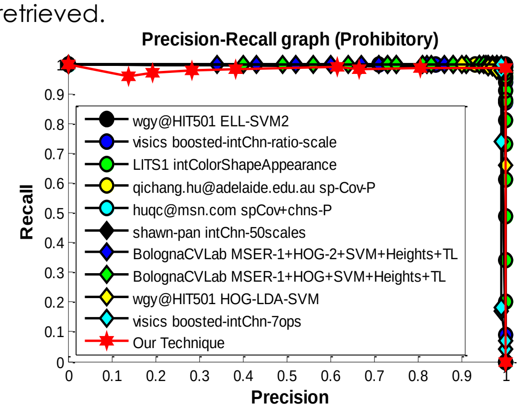


Figure 8 The precision-recall curves for the top ten results in GTSDB competition in black lines and proposed technique in a red line (prohibitory category)

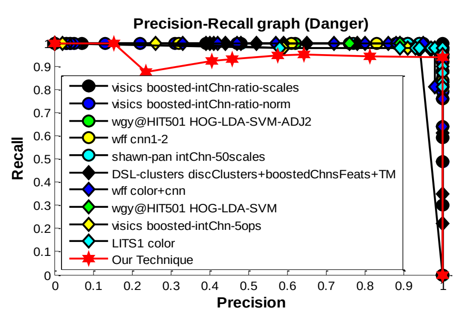


Figure 9 The precision-recall curves for the top ten results in GTSDB competition in black lines and the proposed technique in a red line (danger category)

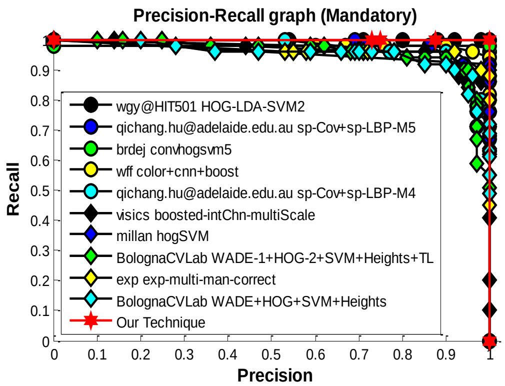


Figure 10 The precision-recall curves for the top ten results in GTSDB competition in Black lines and proposed technique in Red line (mandatory category)

The overall performance of the proposed technique is shown in**Error! Reference source not found.** 0 according to its precision, recall and TS shape matching percentage.

Table 1 Precision, recall and TS shape matching percentages for the proposed technique

	Precision	Recall	Shape matching
Proposed technique	100%	97.67%	100%

A comparison between the top ten methods in the GTSDB competition and the proposed technique according to the best precision-recall pair value is shown in 0, sorted by the precision value.
It is worth mentioning that the proposed technique fails to detect TSs that are very close to each other. This fact can be attributed to the impossible separation of color and shape of each TS.

According to the mentioned results, the proposed technique can accurately detect over 97% of the TSs found in the 300 images without detecting any ROI that is not a TS. In addition, the shape of the detected TS is accurately recognized without any errors. The proposed technique can be used in all of the three categories found in the GTSDB, unlike other techniques, which provide good results in only one category. A sample TS detection and shape match is shown in 0.

Figure 11 TS detction and shape matching samples (C is for Circle TS and S is for Stop TS)

Table 2 Precision and recall percentages for the proposed technqiue and the top ten methods in the GTSDB competition

Method (Prohibitory category)	Precision	Recall
visics boosted-intChn-ratio-scale	100%	100%
LITS1 intColorShapeAppearance	100%	99%
huqc@msn.com spCov+chns-P	100%	99%
shawn-pan intChn-50scales	100%	99%
Proposed Technique	100%	99%
wgy@HIT501 ELL-SVM2	99%	100%
qichang.hu@adelaide.edu.au sp-Cov-P	99%	100%
visics boosted-intChn-7ops	99%	100%
BolognaCVLab MSER-1+HOG-2+SVM+Heights+TL	99%	99%
BolognaCVLab MSER-1+HOG+SVM+Heights+TL	99%	99%
wgy@HIT501 HOG-LDA-SVM	99%	98%
Method (Danger category)	**Precision**	**Recall**
visics boosted-intChn-ratio-scales	100%	100%
visics boosted-intChn-ratio-norm	100%	98%
shawn-pan intChn-50scales	100%	98%
visics boosted-intChn-5ops	100%	98%
LITS1 color	100%	98%
wgy@HIT501 HOG-LDA-SVM-ADJ2	100%	97%
wff cnn1-2	100%	97%
DSL-clusters discClusters+boostedChnsFeats+TM	100%	97%
wff color+cnn	100%	95%
wgy@HIT501 HOG-LDA-SVM	100%	95%
Proposed Technique	100%	94%
Method (Mandatory category)	**Precision**	**Recall**
wgy@HIT501 HOG-LDA-SVM2	100%	100%
Proposed Technique	100%	100%
brdej convhogsvm5	100%	98%
wff color+cnn+boost	100%	94%
millan hogSVM	100%	92%
exp exp-multi-man-correct	98%	90%
BolognaCVLab WADE-1+HOG-2+SVM+Heights+TL	95%	90%
qichang.hu@adelaide.edu.au sp-Cov+sp-LBP-M5	94%	92%
visics boosted-intChn-multiScale	92%	96%
BolognaCVLab WADE+HOG+SVM+Heights	92%	90%
qichang.hu@adelaide.edu.au sp-Cov+sp-LBP-M4	90%	96%

A blurred TS is easily detected using the proposed technique, as it detects the TS by both its color and shape information (0).

Figure 12 Blurred TS detection and shape matching (NE is for No Entry TS)

4.0 CONCLUSIONS

In the GTSDB competition, the selection of the best performance team was based on the highest accuracy in each category. In the proposed system, the results are presented for the all of the testing images across all of the categories with the same technique.

The proposed TS detection and shape recognition technique is evaluated on the GTSDB. The technique is based on the simple bitwise XOR operator, which makes the detection process fast and reliable. In addition, the proposed technique reduces the complexity found in any other detection technique, making it easy to be designed and implemented in real life. A comparison between the top ten teams in the GTSDB competition and the proposed technique was conducted. Based on this comparison, the proposed technique has shown its efficiency and reliability with an overall accuracy of over 97%, and a shape match accuracy of 100%. Hence, the proposed technique can be used in detecting TSs in a variation of illumination scenarios, as in bright and sunny, or dark and foggy weather. Moreover, if the TS is blurred, faded or partially occluded, the proposed system is able to detect it.

The proposed shape matching facilitates the recognition of the shape of the TS. This approach, which makes the understating of the TS component easier, has not been utilized in the previously reported works.

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