2011 Sixth International Conference on Image and Graphics

A Robust Traffic Sign Recognition System for Intelligent Vehicles

Zhixie Chen
School of Information Science and Technology
University of Science and Technology of China
Hefei 230027
chzhixie@mail.ustc.edu.cn

Jing Yang
Institute of Intelligent Machines
Chinese Academy of Sciences
Hefei 230031
jyang@iim.ac.cn

Bin Kong
Institute of Intelligent Machines
Chinese Academy of Sciences
Hefei 230031
bkong@iim.ac.cn

Abstract—**The recognition of traffic signs in natural environment is a challenging problem in computer vision because of the influence of weather conditions, illumination, locations, vandalism and other factors. In this paper, we propose a robust traffic signs recognition system for the real utilization of intelligent vehicles. The proposed system is divided into two phases. In the detection and coarse classification phase, we employ the Simple Vector Filter algorithm for color segmentation, Hough transform and curve fitting approaches in shape analysis to divide traffic signs into six categories according to the color and shape properties. In the refined classification phase, the Pseudo-Zernike moments features of traffic sign symbols are selected for classification by support vector machines. The rationality and effectiveness of the proposed system is validated from great number of experiments.**

Keywords-traffic sign recognition; simple vector filter; Pseudo-Zernike moments; support vector machines

I. INTRODUCTION

With the rapid urbanization and the increasing number of car ownership, Traffic Safety is becoming increasingly prominent and drawing great attention from the society. As a transport language, traffic sign can be interpreted by drivers with its shape, color, pattern and text. Traffic signs are much important and they represent the current traffic situation, show danger, give warnings to drivers and so on. Because of weather conditions, illumination, locations, vandalism and other factors, Traffic Sign Recognition (TSR) system has been a challenge problem for many years as a component of the Advanced Driver Assistance System (ADAS) of intelligent vehicles.

Traffic sign detection and recognition algorithms have drawn considerable research attention in recent years. Generally, traffic signs systems can be divided into two stages: 1) detection and 2) recognition. As the first block of the detection system, a segmentation stage in many works is carried out by set thresholds of some color space to extract the candidate sign from the scene. For this purpose, many works employed several kinds of color spaces, such as RGB [1], HSV/HIS [2, 3], CIElab[4] and YCbCr[5]. Shape based approaches are also developed for traffic sign detection. In [6], Fast Fourier Transform (FFT) was employed to retrieve shape signatures. G. Loy and N. Barnes [7]developed a fast shape-based method for road sign detection. In the recognition stage, there are series of approaches which include Neural Networks [8], Template Matching [9]and Support Vector Machines (SVM) [10]. Merve Can Kus et al. [11] developed a traffic sign recognition system using Scale Invariant Feature Transform (SIFT) and color classification. Kouzani, A. Z. proposed an ensemble learning approach for recognizing traffic signs [12]. Other recognition methods such as Fuzzy Shape recognizer [13] and SimBoost [14] have also been used.

In this paper, we aimed at developing a traffic sign recognition system for the real utilization of intelligent vehicles. Similarly, the proposed system is divided into two phases. In the detection and coarse classification phase, the acquisition image is preprocessed, and then segmented according to the sign properties of color and shape. After that we have the candidate traffic signs to simply divide into six categories in terms of their color and shape information. Then the candidate regions are normalized to a specified size, and then image database are built for training. In the fine classification phase, Pseudo-Zernike moments are selected to represent the feature value of traffic sign symbols and SVM is used for recognition. The system proposed in this paper is out of the ordinary for it not only realizes an entire system for traffic sign detection and recognition, but also covers a wide majority of Chinese traffic signs rather than being restricted to a certain type of signs.

The remainder of the paper is organized as follows. Brief introduction of Chinese traffic signs are given in section 2. Section 3 presents an overview over the system including color segmentation, shape analysis, feature extraction and classification. The experiment results are demonstrated in section 4, followed by conclusions in section 5.

II. CHINESE TRAFFIC SIGNS

Chinese traffic signs can be categorized into four types:

- Prohibitory signs: They are used to prohibit or appropriately restricted on the vehicle according to the situation of streets and traffic. Normally, they are

978-0-7695-4541-7/11 $26.00 © 2011 IEEE
DOI 10.1109/ICIG.2011.58

designed in a circular shape with a thick red rim and a white background.

- Warning signs: they indicate a hazard ahead on the road or remind drivers to take measures to deal with in front of traffic information. Usually, they are equilateral triangles with a black symbol and a yellow background rimmed a black border.
- Mandatory signs: They control the actions of drivers and pedestrians. They are shaped with a complete blue circle and a white arrow or pictogram.
- Indicatory and supplementary signs: These types of signs are characterized by using rectangles with different background colors such as green, or blue etc. with white or black symbols.

As shown in Figure 1, there are 26 classes according to the request by the competition of "Future Challenge of Intelligent Vehicle" of 2010.

III. SYSTEM OVERVIEW

As shown in Figure 2, the proposed system consists of several functional blocks which working together to complete the task of traffic sign recognition. These blocks are simply introduced as follows:

A. Color segmentation

Asakura [15] proposed a new filter----Simple Vector Filter (SVF), which has characteristics that can extract the specific color at high speed and eliminate the outlines at the same time, as shown in Figure 3. The algorithm of SVF is based on the HIS table color. If the vector direction is the same, the corresponding color element would be the same too and then achromatic color could be expressed by the same direction of vector. Accordingly, the SVF is on behalf of the direction of the vector and a corresponding color territory. The center of gravity direction in the triangle is the achromatic color. The vector calculation of achromatic color is given by:

$$F(R,G,B)=\frac{(|R-G|+|G-B|+|B-R|)}{3D} \qquad (1)$$

$F(R,G,B)<1$: Achromatic Color, $F(R,G,B)\geq 1$: Chromatic Color. Here, R , G , B represent the brightness of the respective color, and D is degree of extracting an achromatic color. In our case, we get much better segmentation results by setting D to 20.

In our experiments, we found that this algorithm can do well in separating the color element of red, yellow and blue, and it can achieve better color segment result than traditional used other color space, such as RGB, HSV, HIS, etc. in various weather conditions, namely sunny and cloudy days. Meanwhile, because of the low computational complexity, the SVF color segment method is more suitable for real-time use. According to Figure 3, this three colors

Figure 1. 26 kinds of traffic signs

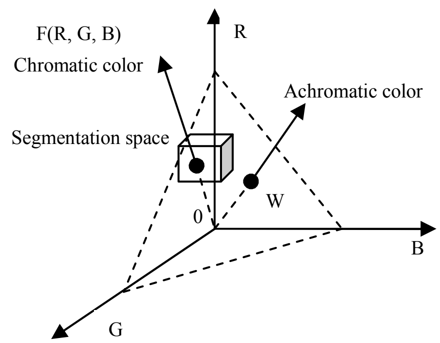


Figure 3. Concept of simple vector filter

could be set to be extreme as (255, 0, 0), (0, 0, 255), (255, 255, 0) in the ideal condition, and the element of the color distributes around the corresponding extreme value in the real time. Under the limited region, shown as following equation (1), it will be stored if the direction of the vector shows significant differences. For each RGB pixel $x = [x_R, x_G, x_B]$, a simple SVF color segment is provided by the following equations:

Red: $x_R - x_G > 40$ and $x_R - x_B > 40$;

Yellow: $x_R - x_B > 50$ and $x_G > 50$;

Blue: $x_B - x_R > 65$ and $x_B > 45$;

As a result, the algorithm of SVF is appropriate to solve the problem of color segmentation of traffic sign and several single color channel images (e.g. red channel image, yellow channel image, blue channel image) can be obtained.

B. Shape analysis and Normalization

After the single color channel images are obtained by the above SVF color segmentation, we use Hough transform and curve fitting approaches to extract candidate traffic sign regions by having ellipse and triangle detections in red channel image, rectangle and ellipse detections in blue channel image, triangle and rectangle detections in yellow channel image. As shown in Figure 4, according to the characteristics of different color and shape, traffic signs are coarsely classified into six classes, i.e. "RC" class, "RT" class, "BR" class, "BC" class, "YT" class and "YR" class. Meanwhile, some corresponding restrictions are imposed on

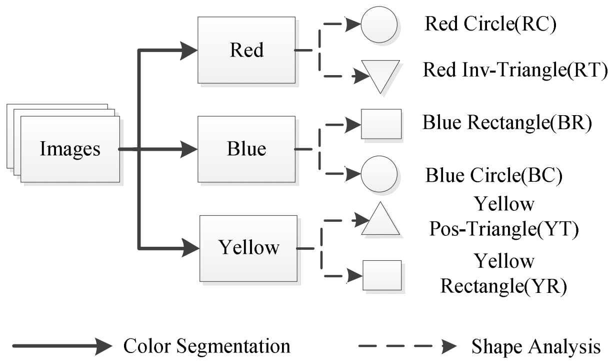


Figure 4. Shape analysis and coarse classification

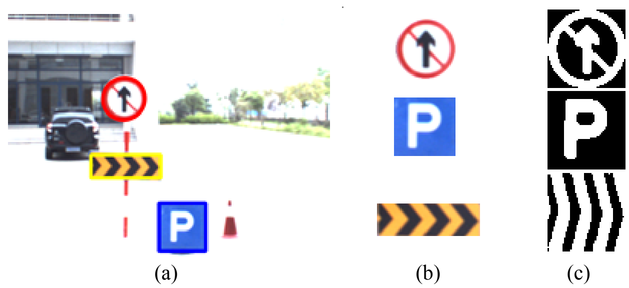


Figure 5. Shape analysis and normalization. (a) Results of shape analysis and traffic signs labeling; (b) Extracted ROI images; (c) ROI normalization and binarization (51*51 pixels).

different shape detections, such as region size and location limitation, etc.

Because of the difference of candidate region size, position, orientation and other factors, the candidate regions in binary channel images need to be normalized before calculating Pseudo-Zernike moments features though they have properties of translation, scale and rotation invariance. In order to normalize the candidate regions of traffic sign into uniform size, the bicubic interpolation algorithm is employed in this paper to standardize the dimension of ROI (Region of Interest) irrespective of its scale in original image. Figure 5 depicts results indicating shape analysis, ROI extraction, and ROI normalization and binarization.

C. *Feature extraction*

With excellent properties for invariances of translation, rotation and scale, moments which firstly introduced by Hu [16], have been widely used in computer vision applications such as image analysis, patter recognition and image reconstruction. Pseudo-Zernike Moments [17] are the set of orthogonal Pseudo-Zernike polynomials defined over a unit circle in polar coordinates. Due to the orthogonal property, Pseudo-Zernike Moments are robust to noise and minimize the amount of information redundancy.

Mathematically, the two-dimensional Pseudo-Zernike moments of order p with repetition q over $D=\{(p,q)\,|\,0\le p\le\infty, |q|\le p\}$ are defined as:

$$Z_{pq}=\frac{p+1}{\pi}\iint\limits_{x^2+y^2\le 1} f(x,y)R_{pq}(r_{xy})\exp(-jq\theta_{xy})dxdy \qquad (2)$$

where $f(x,y)$ is a discrete image intensity function, $r_{xy}=\sqrt{x^2+y^2}$, $\theta_{xy}=arc\tan(y/x)$, and $R_{pq}(r)$ is given as:

$$R_{pq}(r)=\sum_{s=0}^{(p-|q|)}(-1)^s\frac{(2p+1-s)!}{s!(p+|q|+1-s)!(p-|q|-s)!}r^{p-s} \qquad (3)$$

An efficient algorithm for fast computation of Pseudo-Zernike moments [18] is given as follows:

$$R_{pq}(r)=\sum_{k=q}^{p}A_{pqk}r^k \qquad (4)$$

where $k=p-s$, and $A_{pqk}=\frac{(-1)^{p-k}(p+k+1)!}{(p-k)!(k+q+1)!(k-q)!}$.

The recurrence relations as follows can be used for efficient computation of A_{pqk}:

$$A_{pqp}=1$$
$$A_{p(q-1)k}=A_{pqk}\frac{k+q+1}{k-q+1} \qquad (5)$$
$$A_{pq(k-1)}=-A_{pqk}\frac{(k+q+1)(k-q)}{(p+k+1)(p-k+1)}$$

Algorithm 1 is used to illustrate the calculation of Pseudo-Zernike moments based feature representation.

Algorithm 1 *PZM_Feature* (*ROI*, *N*)

Input: *ROI* {the ROI image of size 51*51} and *N* {a set of the Pseudo-Zernike moments order}
Output: *PZM_Feature* {the feature vectors of ROI image}
1: Put the *ROI* into the unit circle in polar coordinate space, take the center as the origin;
2: Initialize *PZM_Feature* = [ ];
3: **while** (p , q) in N **do**
4: Calculate A_{pqk} using Equation (5);
5: Calculate R_{pq} using Equation (4);
6: Calculate Z_{pq} using Equation (2);
7: *PZM_Feature* = [Z_{pq}];
8: **end while**
9: **return** *PZM_Feature*;

D. *Classification*

Support vector machines (SVM) is a set of related supervised learning methods based on the Statistical Learning Theory, which was first introduced by Vapnik [19].

A support vector machine constructs a hyper plane or set of hyper planes in a high dimensional space, which can be used for classification. A good separation is achieved by the hyper plane that has the largest distance to the nearest training data points of any class, namely functional margin. The support vector machine learns a separating hyper plane to maximize the margin for a better classification capacity.

Because of their good capacity compared with conventional classifiers, SVM is widely used for classification and regression analysis.

As a basic training principle, a SVM classifier analyzes and finds an optimal hyper plane that correctly while maximizing the distance of either class from the margin. The function of the hyper plane is defined by the relation:

$$f(x)=\sum_{i=1}^{l} y_i a_i K(x_i, x)+b \tag{6}$$

where x is the input vector, l is training samples. Here training vectors x_i are mapped into a higher (maybe infinite) dimensional space by the function ϕ . Furthermore, $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is known as a kernel function.

Though new kernels are being proposed by researchers, we should know the following four basic kernels:

- linear: $K(x_i, x_j) = x_i^T x_j$
- polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + c)^d, \gamma > 0$
- Gaussian radial basis function (RBF): $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0$
- sigmoid: $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + c)$

where γ, c , and d are kernel parameters.

The effectiveness of SVM depends on the selection of kernel, the kernel parameters, and soft margin parameter. In this work, we make a common choice which is a Gaussian kernel with a single parameter γ , and using Shrinking method to speed up the training process. For the optimization problem, the error tolerance of KKT is set to 10^{-3}, parameters are obtained through 10 times cross validation.

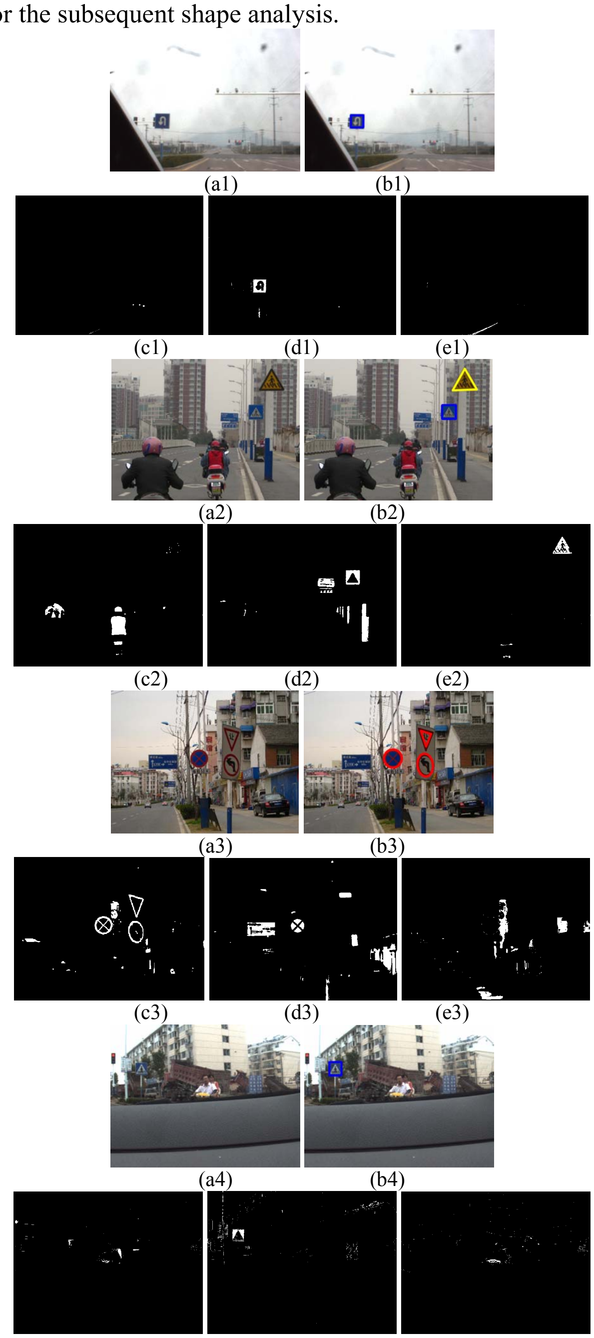
Due to the rotation invariance of Pseudo-Zernike Moments, it is difficult to distinguish “straight only”, “keep left”, and “keep right” of blue circle signs by the moments features. So a second judgment is need for these three kinds of signs by a simple template matching algorithm.

IV. EXPERIMENT RESULTS

In order to test the performance of the proposed approach, a dataset of 2643 raw images of traffic signs are used for testing. These pictures were captured under various weather conditions, at different times and locations. A camcorder mounted in front of the windscreen was used for this task. All of them are RGB images with 640*480 pixels. The training database consists of 600 binary images of size 51x51 pixels are used for training of the SVM after calculating the invariant features.

The traffic sign recognition system has been developed based on visual C++ using the LIBSVM [20] and Intel® Open Source Computer Vision Library (OpenCV) [21]. In our system, two mainly phases are proposed that are detection and coarse classification phase and refined classification phase.

Figure 6 depicts experimental results for both color segmentation and shape analysis. The candidate regions are labeled by corresponding color and shape. Because of the different weather conditions, illumination changes greatly among these original images (Column a), which can be obviously seen from Figure 6 (a1), (a3), (a6) and (a7). We also have the changes in scale and rotation, e.g. Figure 6 (a3), (a7). At the end of this experiment, we get perfect results. However, it can be found in Figure 6 (e5) and (e6) that some yellow information shift to the red channel as a result of different illumination. In these cases, we merge the red and yellow channel together to get robust binary channel image for the subsequent shape analysis.



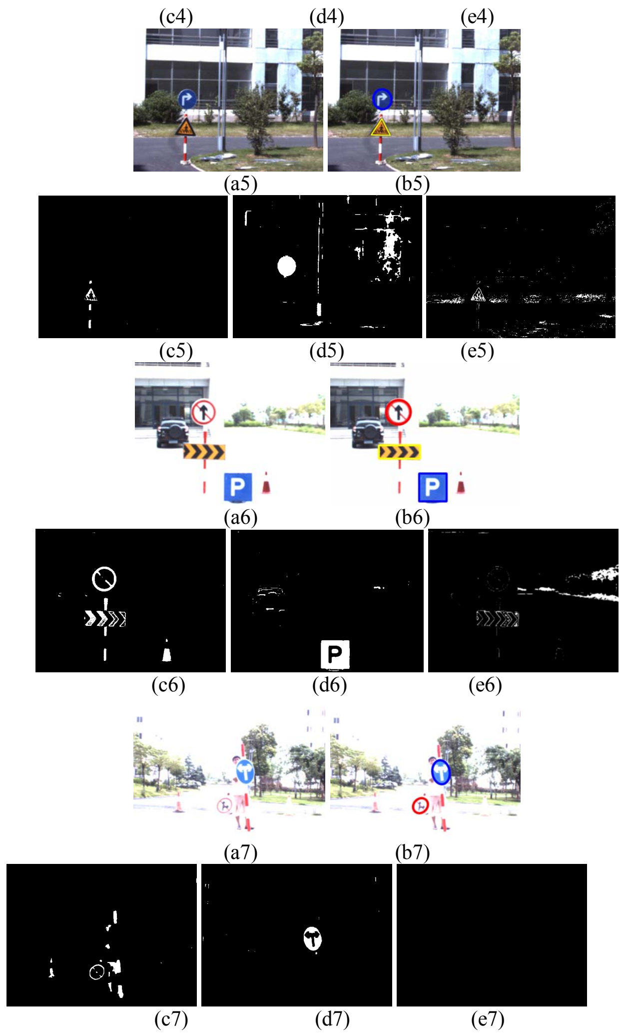


Figure 6. Results of experiment for color segmentation and shape analysis. (Column a) Original images; (Column b) Results using the shape analysis and candidate region labeling; (Column c) Red channel images; (Column d) Blue channel images; (Column e) Yellow channel images.

Table 1 summarizes the experimental results of traffic signs detection. These testing images are divided into two types, i.e. "Sunny", "Cloudy" according to different illuminations. Total Images (TI) means the total number of images. Total Signs (TS) has a similar meaning. Correct Detection (CD) is the number of traffic signs correctly detected. False Detection (FD) indicates the number of signs wrongly detected. Hit Rate (HR) equals CD divided by TS.

Table 2 summarizes the experimental results of traffic signs recognition. True Positive (TP) denotes the number of traffic signs correctly classified in the refined classification phase. Accordingly, False Positive (FP) indicates the number of signs wrongly classified. False Negative (FN) is the number of noise objects wrongly classified as traffic signs. Accuracy Rate (AR) equals TP divided by TS.

TABLE I. TRAFFIC SIGN DETECTION RESULTS

Weather Condition	TI	TS	CD	FD	HR
Sunny	976	2173	2113	269	97.2%
Cloudy	1667	2614	2562	299	98.0%

TABLE II. TRAFFIC SIGN RECOGNITION RESULTS

Traffic Signs	TS	TP	FP	FN	AR
Red Circle	1412	1322	90	191	93.6%
Red Inv-Triangle	305	287	18	17	94.1%
Blue Rectangle	781	715	66	109	91.5%
Blue Circle	1618	1495	123	206	92.4%
Yellow Pos-Triangle	358	332	26	24	92.7%
Yellow Rectangle	313	283	30	21	90.4%

From Table 2, it is necessary to point out that the accuracy rate of traffic sign recognition is over 90%. Owing to its distinctiveness and uniqueness, the accuracy rate of the RT kind sign recognition achieves the best result which is 94.1%. Obviously, experimental results indicate that our system is accurate and robust. At same time it is found that there are a small amount of images with the trouble in detection and recognition. After careful observation and analysis of these images, the reasons in missed or false detection and wrong classification are as follow: severely faded traffic signs, highlights, occlusion and the influence of advertising sign.

Time performance of the system is as follows: color segmentation takes 60ms in average, while circle recognition takes 100ms, and triangle and rectangle sign recognition take 150ms. And Lenovo Zhaoyang E42 is used in these experiments.

V. CONCLUSION

In this paper, we propose a robust traffic sign recognition system for intelligent vehicles. In the detection and coarse classification phase, we get normalized ROI and divide traffic signs into six sub-classes by using the algorithms of color segmentation and shape analysis. In the refined classification phase, we calculate the Pseudo-Zernike moments features and have traffic signs to divide into appropriate categories with the SVM classifier. Besides, due to the moments' rotation invariance, we use a simple template matching algorithm to make a second judgment for some kinds of signs. Experiment results show that the proposed system can accurately and rapidly recognize traffic signs in a natural environment, and it covers a wide majority of Chinese traffic signs rather than being restricted to a certain type of signs. Future work will include systematic research on more abominable illumination conditions such as dark night, rainy days, etc.

ACKNOWLEDGMENTS

This work was supported by National Natural Science Foundation of China under grant No. 60875076.

REFERENCES:

[1] A. Soetedjo and K. Yamada, "Fast and robust traffic sign detection," NEW YORK: IEEE, 2005, pp. 1341-1346.

[2] P. Medici, C. Caraffi, E. Cardarelli, P. P. Porta and G. Ghisio, "Real Time Road Signs Classification," 2008 IEEE INTERNATIONAL CONFERENCE ON VEHICULAR ELECTRONICS AND SAFETY, pp. 303-308.

[3] W. Y. Wu, T. C. Hsieh and C. S. Lai, "Extracting Road Signs using the Color Information,". vol. 26 CANAKKALE: WORLD ACAD SCI, ENG & TECH-WASET, 2007, pp. 282-286.

[4] L. D. Lopez and O. Fuentes, "Color-based road sign detection and tracking,". vol. 4633 BERLIN: SPRINGER-VERLAG BERLIN, 2007, pp. 1138-1147.

[5] M. L. Eichner and T. P. Breckon, "Integrated Speed Limit Detection and Recognition from Real-Time Video," NEW YORK: IEEE, 2008, pp. 964-969.

[6] P. Gil-Jimenez, S. Lafuente-Arroyo, H. Gomez-Moreno, F. Lopez-Ferreras and S. Maldonado-Bascon, "Traffic sign shape classification evaluation II: FFT applied to the signature of Blobs," 2005 IEEE Intelligent Vehicles Symposium Proceedings, pp. 607-612.

[7] G. Loy and N. Barnes, "Fast shape-based road sign detection for a driver assistance system," Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on,0028-02-20 2004, ppp. 70- 75 vol.1.

[8] M. S. Hossain, M. M. Hasan, M. A. Ali, M. H. Kabir and A. B. M. S. Ali, "Automatic detection and recognition of traffic signs," Robotics Automation and Mechatronics (RAM), 2010 IEEE Conference on2010, ppp. 286-291.

[9] Y. P. Wang, M. P. Shi and T. Wu, "A Method of Fast and Robust For Traffic Sign Recognition," PROCEEDINGS OF THE FIFTH INTERNATIONAL CONFERENCE ON IMAGE AND GRAPHICS (ICIG 2009), pp. 891-895.

[10] S. M. Bascon, J. A. Rodriguez, S. L. Arroyo, A. F. Caballero and F. Lopez-Ferreras, "An optimization on pictogram identification for the road-sign recognition task using SVMs," COMPUTER VISION AND IMAGE UNDERSTANDING, vol. 114, pp. 373-383.

[11] M. C. Kus, M. Gokmen and S. Etaner-Uyar, "Traffic Sign Recognition using Scale Invariant Feature Transform and Color Classification," 23RD INTERNATIONAL SYMPOSIUM ON COMPUTER AND INFORMATION SCIENCES, pp. 117-122.

[12] A. Z. Kouzani, "Road-sign identification using ensemble learning," 2007 IEEE INTELLIGENT VEHICLES SYMPOSIUM, VOLS 1-3, pp. 542-547.

[13] H. Fleyeh, "Traffic Sign Recognition by Fuzzy Sets," NEW YORK: IEEE, 2008, pp. 283-288.

[14] A. Ruta, Y. M. Li and X. H. Liu, "Robust Class Similarity Measure for Traffic Sign Recognition," IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, vol. 11, pp. 846-855.

[15] T. Asakura, Y. Aoyagi and O. K. Hirose, "Real-time recognition of road traffic sign in moving scene image using new image filter," SICE 2000: PROCEEDINGS OF THE 39TH SICE ANNUAL CONFERENCE, INTERNATIONAL SESSION PAPERS, pp. 13-18.

[16] H. Ming-Kuei, "Visual pattern recognition by moment invariants," Information Theory, IRE Transactions on, vol. 8, 1962-01-01 ,pp. 179-187.

[17] C. H. Teh and R. T. Chin, "On image analysis by the methods of moments," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 10, 1988-01-01 ,pp. 496-513.

[18] C. W. Chong, P. Raveendran and R. Mukundan, "An efficient algorithm for fast computation of pseudo-Zernike moments," INTERNATIONAL JOURNAL OF PATTERN RECOGNITION AND ARTIFICIAL INTELLIGENCE, vol. 17, pp. 1011-1023.

[19] C. CORTES and V. VAPNIK, "SUPPORT-VECTOR NETWORKS," MACHINE LEARNING, vol. 20, pp. 273-297.

[20] C. Chang and C. J. Lin, “LIBSVM: a library for support vector machines”, 2009, available at: www.csie.ntu.edu.tw/~cjlin/libsvm.

[21] Intel Corporation, “Open Source Computer Vision Library”, Reference Manual, Copyright © 1999-2001, available at: www.developer.intel.com.

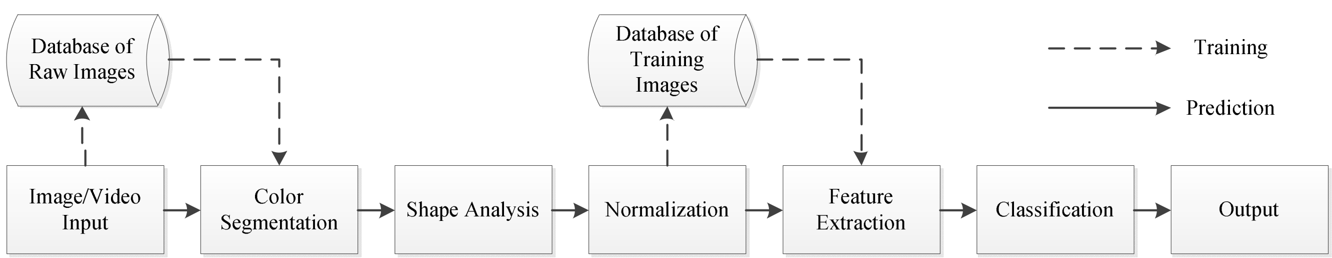


Figure 2. Framework of the proposed system