Automated Inventory and Analysis of Highway Assets, Phase-II

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ABSTRACT

Road sign plays an important role in highway system management by providing drivers and road users guidance, warning and other driving related information. Proper sign maintenance and inventory is therefore necessary. Sign inventory system is an essential tool for infrastructure management and maintenance. Currently, sign inventory is mostly conducted by human observation of the digital images of roadway scenes. Automated system would substantially improve the processing speed and accuracy of two key processing tasks, sign detection and sign classification, since the human observation of the large amount of images is tedious, error-prone and time-consuming. The research in this final report emphasizes on the study of the classification. Classification is to categorize signs into proper classes, which is important and also more difficult for automation in the automated sign inventory system. The most frequently used technique in previous research for classification is neural network. However, neural network has the local minimum problem. In addition, neural network lacks explainable inner theoretical rule which brings difficulty to fine tune the performance of the model. This research presents a method for sign classification which combines feature extraction, Support Vector Machine (SVM), and multi-class classification. SVM is a statistical learning method based on Vapnik-Chervonenkis (VC) dimension and structural minimum principle. It is supposed to overcome the aforementioned two drawbacks of neural network method. The feature extraction is accomplished by Principal Component Analysis (PCA) which reduces the dimension of the image as well as keeping the most important features. Preliminary experimental result presented in the report demonstrates that the SVM method has potential to solve the road sign classification problem.

INTRODUCTION

Road sign is the most important traffic control device. It notifies road users of regulations and provides warning and guidance to them. It helps maintain a safe, uniform and efficient operation of all elements of the traffic stream. Proper maintenance and management of the roadway system partly depends on a well maintained road sign inventory database. At this time, manual processing is the most straightforward and common means to collect road signs into a database for asset management purposes. This process is tedious, slow and prone to errors.

Automated road sign recognition through digital imaging and digital image processing will tremendously improve processing speed and accuracy for sign inventory, and decrease the reliance on the manual effort. Digital images captured from one or multiple cameras mounted on top of or inside the roadway survey vehicle have been widely used in the roadway dataset collection. It is commonly referred as the ROW imaging system. The acquired images can be processed with automated techniques for road sign recognition. Road sign recognition belongs to the domain of computer vision. However, the field of automated recognition of road signs is quite recent (2). Various computer vision methods were applied for the detection of objects in outdoor scenes. Since then, many research groups and companies conducted various research projects in the field. Different techniques have been used, and substantial improvements have been achieved during the last two decades. Automated recognition of road sign includes two primary phases: Detection and Classification.

Automated detection of the presence of road signs is a relatively mature technique. Most basic detection techniques are segmentation methods based on color and shape properties. Color segmentation methods used include RGB (3), HSI (4, 5), HSV (6), L*a*b (7), and LUV (8) based color space thresholding etc. Techniques with CIECAM97 (9) were also used. Some researchers developed databases of color pixels (10, 11), and hieratical region growing techniques (12). More advanced technique such as fuzzy set (13) or neural network (14) were also found. Shape criterion were then applied consequently, or even simultaneously applied with color criterion.

Only incremental improvements were made in automated sign classification. Sign inventory system normally contains hundreds of different signs. Classification is therefore important since when the presence of a sign is detected, it need to be recognized for content. Neural network and template matching are two major methodologies to classify a sign into its correct class. As a matter of fact, neural network based techniques serve as the majority of the solutions to classification of the sign. Neural network used in Road sign classification include back progagation (15), ART2 (16), Hopfeild (17), and cellular neural networks (18), etc.

The disadvantages of using neural network in road sign recognition are: 1) there is substantial training overhead, and the multi-layer neural networks can not be adapted for on-line application due to their architecture. The target application in road sign inventory system requires real-time processing. 2) Since the architecture is fixed, there is no provision for an increase in the number of classes without a severe redesign penalty, and neural network based techniques cannot recognize new patterns without retraining the entire network. 3) The inner rule is not explainable and it is not easy to fine tune the performance of the system.

Support Vector Machine (SVM) was introduced by Vapnik (19). This method did not receive wide recognition until the recent rapid development of the Statistical Learning Theory and Bayesian arguments. Similar to neural network, SVM includes training and testing. The training task is actually an optimization of a convex cost function. There are no false local minima to complicate the learning process which is one of its advantages over neural network. Another advantage is that this methodology constructs a model which has an explicit dependence on the most informative patterns in the data (the support vector) instead of the vagueness inside of the neural network black box. This property makes the SVM to have a straightforward interpretation. It has recently been successfully applied to a number of applications ranging from particle identification, face identification, and text categorization, to engine knock detection, bioinformatics and database marketing (1).

METHODOLOGIES

The methodology proposed in this research is as follows: first, a standard road sign image library is developed by collecting the road sign images in the field. The images were captured under variant lighting conditions. These images are used for training and testing purposes during the modeling of the SVM. Only a portion of the images in the library were used for training and others for testing. The images were converted into HSV color space first. The images are preprocessed and regions of interest were found by shape and color criteria. To deduct the redundant information in the images, first the images went through a HSV quantization process. Then Principal Components Analysis (PCA) algorithm is applied to extract the features of the regions of interest. These PCA features are input into the SVM model to do the classification. Once the SVM model is set up, proper class is assigned to each testing image. Figure 1 illustrates the classification process.

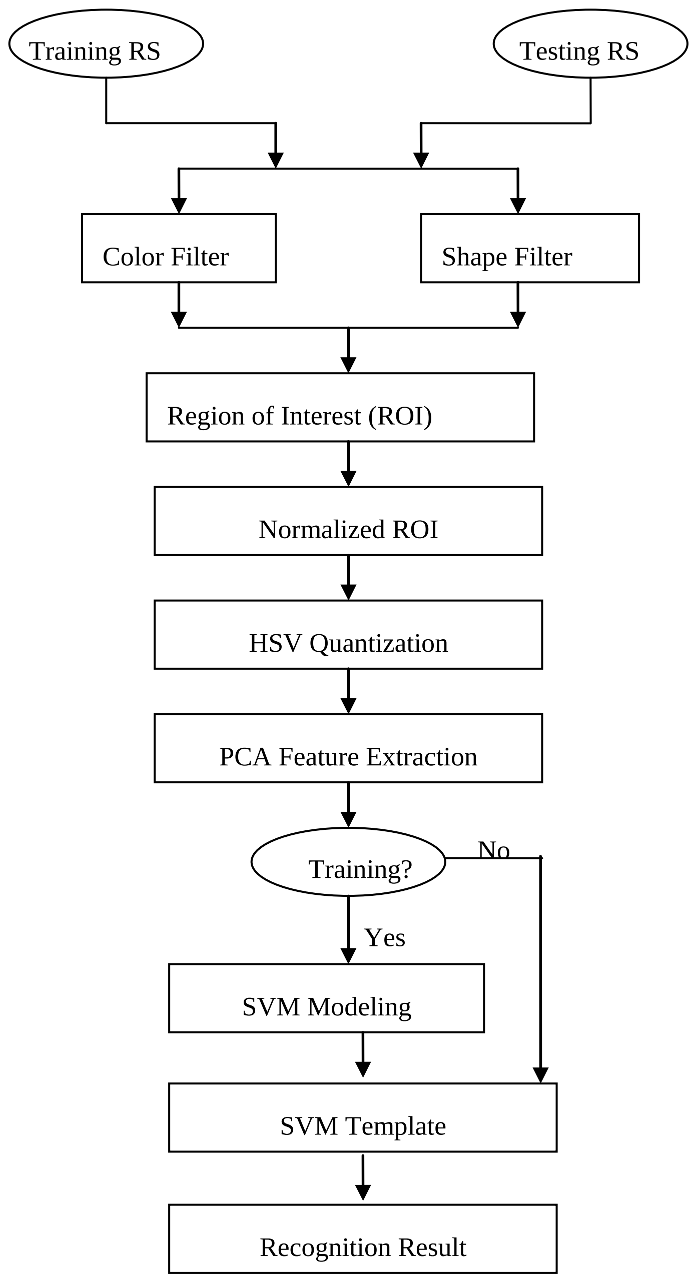

Figure 1. Framework of the SVM based Imaging System

Image Library for Standard Road Sign

The library for standard road signs includes more than 100 types of road signs captured from July 2005 to June 2006 by the researchers at the University of Arkansas. Each road sign has 10 images retrieved under different surroundings. Figure 2 shows 10 images for the Center Lane sign at different locations captured in 10 different conditions.

Figure 2. The sample images in the standard road sign library

Pre-Processing

In Road Sign Recognition System, it is necessary to implement preparing process in order to achieve higher accuracy. Captured images are stored in RGB and need to be converted into HSV (Hue, Saturation, and Value). HSV model is based on human perception, which divides a color space in terms of three constituent components. Hue, the color type, ranges from 0–360 in most applications. Each value corresponds to one color. Examples: 0 is red, 45 is a shade of orange and 55 is a shade of yellow. Saturation, the intensity of the color, ranges from 0 to 100%. 0% means no color, 100% means intense color. Value, the brightness of the color, ranges from 0 to 100. 0 is always black. Depending on the saturation, 100 may be white or a more or less saturated color.

Region of interest would be extracted from the whole image based on color and shape criteria. Color criteria are defined based on experiment (20). Shape criteria are defined by the geometrical properties of different shapes. There are four shape types (Octagon, rectangle, triangle, circle and diamond) and five color types (red, blue, brown, green and black and white) considered in this model. Figure 3 shows that a region of interest is extracted after the use of preparing filter.

a) Original Image b) After Color Filter c) Region of Interest

Figure 3. The Detection of Region of Interest

Quantization of HSV

When region of interest has dramatically narrowed down the study area in the original image, this part of data still has a lot of redundant information which can slow the analysis. In order to make calculation more computing efficient, HSV quantization filter is applied to various intervals. Hue value is cataloged into 16 levels, saturation value into 4 levels and value into 4 levels.

$$S = \begin{cases} 0 & s \in (0,0.15) \\ 1 & s \in (0.15,0.4) \\ 2 & s \in (0.4,0.75) \\ 3 & s \in (0.75,1) \end{cases} \qquad (1)$$

$$v = \begin{cases} 0 & v \in (0,0.15) \\ 1 & v \in (0.15,0.4) \\ 2 & v \in (0.4,0.75) \\ 3 & v \in (0.75,1) \end{cases} \qquad (2)$$

$$h = \begin{cases} 0 & h \in (345,15) \\ 1 & h \in (15,25) \\ 2 & h \in (25,45) \\ 3 & h \in (45,55) \\ 4 & h \in (55,80) \\ 5 & h \in (80,108) \\ 6 & h \in (108,140) \\ 7 & h \in (140,165) \\ 8 & h \in (165,190) \\ 9 & h \in (190,220) \\ 10 & h \in (220,255) \\ 11 & h \in (255,275) \\ 12 & h \in (275,290) \\ 13 & h \in (290,316) \\ 14 & h \in (316,330) \\ 15 & h \in (330,345) \end{cases} \quad \text{..........}(3)$$

Then an integration matrix will be retrieved based on three components.

$$L = h * Q_s * Q_v + Q_s s + v \quad \text{..........}(4)$$

Where Q_s、Q_v are weights for s and v components.

Let Q_s = 4 , Q_v = 4 ,equation (4) becomes

$$L = 16h + 4s + v \quad \text{..........}(5)$$

Equation (5) shows that after applying the quantization filter, the influence from saturation (s) and brightness (v) components will be decreased. Thus the image with various colors would be detected robustly. This process also decreases the dimensionality of the data.

PCA algorithm

PCA, first presented by H. Hotelling (21), is an orthogonal linear transformation that converts the data to a new coordinate system, by which the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

PCA can be used for dimensionality reduction in an image data set, represented in a pixel matrix form, by retaining those characteristics of the data set that contribute most to its variance. This property makes it a good tool to extract the features of the road sign images. PCA involves the computation of the eigenvalue decomposition or singular value decomposition of a data set, usually after mean centering the data for each attribute. Then the PCA features, obtained as the first several principal components, can be used in image interpretation and classification. These features later can be input into the SVM model to conduct the road sign classification.

For a road sign with $w \times h$ candidate region image, first it is converted into a $M = w \times h$ vector, M is the dimension of the vector. Let N be the sample number in the training data, then the distribution matrix

$$S_t = \sum_{i=1}^{N} (X_i - \mu)(X_i - \mu)^T \quad \text{...(6)}$$

Where μ is the average image vector in the training data set. $\mu = \frac{1}{N}\sum_{i=1}^{N} X_i$.

$$\text{Let } X = [X_1 - \mu, X_2 - \mu, \ldots, X_N - \mu] \quad \text{,...(7)}$$

then $S_t = XX^T$. Since S_t is a symmetrical matrix, it can be written as $S_t = W \Lambda W^T$. If a linear transform is applied to X as $Y = W^T X$, then the covariance matrix of Y becomes

$$\sum\nolimits_Y = YY^T = W^T X X_T W = \Lambda \quad \text{..(8)}$$

The redundant data in the matrix is removed and only the diagonal data is left. By normalizing each column in the W and it becomes $[W_1, W_2, \ldots, W_N]$ which can form a sub space, the projection of road sign vector P_i to this sub space: $Q = W^T P_i$, therefore:

$$P_i = WQ = \sum_{i=1}^{K} W_i Q_i + \sum_{i=K+1}^{N} W_i Q_i \quad \text{..(9)}$$

If only the first K projections are used, the error of the reconstruction of the image is $e = \sum_{i=K+1}^{N} \lambda_i$, where λ_i is the characteristic value of the matrix S_i. Therefore, if the characteristic values are sorted in a descending order, the first K characteristic vectors can be used to construct a space and the projection of the road sign candidate image in this space will keep the most important feature of the image. In this manner, dimension of the data is deducted from M to K while still maintaining the most important features of the road sign image. These characteristic vectors are later input into the SVM model to conduct the classification.

SVM classification

The basic concept of SVM is to transform the input vectors to a higher dimensional space Z by a nonlinear transform, and then an optical hyperplane which separates the data can be found. This hyperplane should have the best generalization capability. As shown in Figure 4, the black dots and the white dots are the training dataset which belong to two classes. The Plane H series are the hyperplanes to separate the two classes. The optical plane H is found by maximizing the margin value $2/\|w\|$. Hyperplanes H_1 and H_2 are the planes on the border of each class and also parallel to the optical hyperplane H. The data located on H_1 and H_2 are called support vectors.

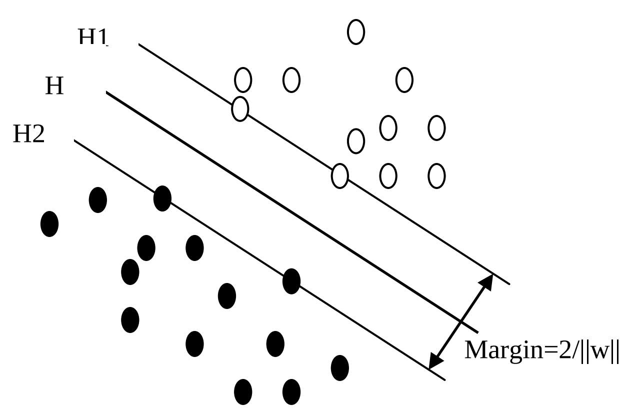

Figure 4 The SVM binary classification

For training data set $(x_1, y_1),...,(x_l, y_l), y_i \in \{-1,1\}$, to find the optical hyperplane H, a nonlinear transform, $Z = \Phi(x)$, is applied to x, to make x become linearly dividable. A weight w and offset b satisfying the following criteria will be found:

$$\begin{cases} w^T z_i + b \geq 1, & y_i = 1 \\ w^T z_i + b \leq -1, & y_i = -1 \end{cases} \quad \text{......(10)}$$

i.e.

$$y_i(w^T z_i + b) \geq 1, \quad i = 1,2,...,l \quad \text{......(11)}$$

Assume that the equation of the optical hyperplane H (Fig.4) is $w_0{}^T z + b_0 = 0$, then the distance of the data point in any of the two classes to the hyperplane is:

$$\rho(w,b) = \min_{x|y=1} \frac{z^T w}{\| w \|} - \max_{x|y=-1} \frac{z^T w}{\| w \|} \quad \text{......(12)}$$

A w_0 is to be found to maximize

$$\rho(w_0, b_0) = 2 / \| w_0 \| = 2 / \sqrt{w_0{}^T w_0} \quad \text{......(13)}$$

Then the search of the optimal plane H turns to a problem of a second order planning problem.

$$\min_{w,b} \Phi(w) = \frac{1}{2}(w^T w) \quad \text{......(14)}$$

Subject to $y_i(w^T z_i + b) \geq 1, \quad i = 1,2,...,l$ ......(15)

If the sample data is not linearly dividable, find the minimum value of

$$\Phi(w) = \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \quad \text{......(16)}$$

Whereas ξ can be understood as the error of the classification and C is the penalty parameter for this term. By using Lagrange method, the decision function of

$$w_0 = \sum_{i=1}^{l} \lambda_i y_i z_i \text{ ....(17)}$$

will be

$$f = \mathrm{sgn}[\sum_{i=0}^{l} \lambda_i y_i (z^T z_i) + b] \text{ ....(18)}$$

From the functional theory, a non-negative symmetrical function $K(u,v)$ uniquely define a Hilbert space H, K is the rebuild kernel in the space H:

$$K(u,v) = \sum_i \alpha\varphi_i(u)\varphi_i(v) \text{ ....(19)}$$

This stands for an internal product of a characteristic space:

$$z_i^T z = \Phi(x_i)^T \Phi(x) = K(x_i, x) \text{ ....(20)}$$

Then the decision function can be written as:

$$f = \mathrm{sgn}[\sum_{i=1}^{l} \lambda_i y_i K(x_i, x) + b] \text{ ....(21)}$$

The development of a SVM road sign classification model depends on the selection of kernel function K. There are several kernels that can be used in Support Vector Machines models. These include linear, polynomial, radial basis function (RBF) and sigmoid function:

$$K(x_i, x_j) = \begin{cases} x_i^T x_j & \textit{Linear} \\ (\gamma x_i^T x_j + coefficient)^{\mathrm{degree}} & \textit{Polynomial} \\ \exp(-\gamma \mid x_i - x_j \mid^2 & \textit{RBF} \\ \tanh(\gamma x_i^T x_j + coefficient) & \textit{Sigmoid} \end{cases} \text{ ....(22)}$$

The RBF is by far the most popular choice of kernel types used in Support Vector Machines. This is mainly because of their localized and finite responses across the entire range of the real x-axis.

Improper kernel function might generate poor performance. Currently there is no effective "learning" method to choose a proper kernel function for a specific problem. The selection is decided by the experiment result at this time. In our proposed system, two kernel functions are tested: Radial Basis Function-RBF and Polynomial Function.

$$K_{poly}(x_1, x_2) = (x_1 * x_2 + 1)^p \quad \text{.......}(23)$$

$$K_{RBF}(x_1, x_2) = \exp(-p \| x_1 - x_2 \|^2) \quad \text{.......}(24)$$

Due to its better performance, RBF was chosen as the kernel function in the model.

Multi-class SVM classification algorithm

SVM is designed to solve a binary classification problem. For a road sign inventory problem, which is a multiple classification problem, classification is accomplished through combinations of binary classification problems. There are two ways to do that: one vs. one or one vs. the other. The first one means class one to other k-1 class. By this means k(k-1) hyperplanes can be obtained. The second one means that the n^{tl} classifier is obtained by solving the n^{tl} sample and the remaining k-1 samples. By this method, k hyperplanes can be obtained. The latter method was adopted in the proposed system. Let the k^{tl} algorithm called K_c, for an m-sample problem, a binary SVM classifier $u_k(x)$ can be found to separate K_c and other algorithm. Then a multi-class classifier L(x) is obtained. For an arbitrary input x:

$$L(x) = \arg\max_{l} \{u_l(x)\} \quad \text{.......}(25)$$

Whereas: $$u_l(x) = \sum_{j=1}^{l_k} y_{lj} a_{lj} K(x_{lj,} x) - b_l \quad \text{.......}(26)$$

The shortcoming of this algorithm is that some testing data might be assigned to several different classes at the same time. To solve this problem, the system provides top 5 candidate results for each testing sample.

For training and testing, 10 feature parameters were obtained using PCA feature extraction. In the training process, the feature vectors for different road sign types were labeled accordingly, such as 0, 1, 2, L etc. Same road sign has the same labels. K different hyperplanes will be obtained for a k-class road sign feature vectors after SVM training. This is accomplished by using binary SVM to obtain the classifying function $u_j(x)$ and separating the j^{th} road sign feature vectors from other road sign types.

During testing, sample z is assigned to its class, the value of $u_l(x)$ in equation (26) need to be calculated, whereas l is from 1 to k. After the labeling $l_{(}$ for L(x) is obtained, the nearest five or more values to $l_{(}$ are selected from{$u_l(x)$} as the road sign candidates.

EXPERIMENT RESULT

To test the performance of the color feature extraction using PCA, the road sign images in the standard sign library are tested. The color features of the images are extracted using PCA and input to SVM as the input vector. The images are trained with a one vs. the other method. For each road sign type, average 20 images are used for training to testing. LIBSVM was employed for classifying training. LIBSVM is integrated software for support vector classification developed by Chih-Chung Chang and Chih-Jen Lin (22). The following procedure is adopted to obtain the best performance in the experiment:

1) Transform the feature vectors obtained from PCA algorithm to the format of SVM software
2) Scale each attribute of the data to the range [-1,1]. This is to avoid attributes in greater numeric ranges dominate those in smaller numeric ranges which might bring overflow during the calculation
3) Select the RBF kernel $K(x,y) = e^{-\gamma\|x-y\|^2}$ due to its good performance
4) Use cross-validation to find the best parameter C and γ whereas C is the penalty parameter for classification error term in equation (16) and γ is a kernel parameter
5) Use the best parameter C and γ to train the whole training set
6) Testing

The table listed below shows the experiment results based on 20 images for road sign classification, each road sign type using 12 images for training and 8 images for testing.

Table 1, Performing Results

Table **No.**	**Classification**	**Number of Types**	**Label**	Accuracy (%)	Testing times
1	Stop Sign	1	“Stop”	98.75	32
2	Yeild Sign	1	“Yield”	95.4	17
3	Do Not Enter Sign	1	“Do Not Enter”	90.8	9
4	Speed Limit (10,15,20,25,30,35,40, 45,50,55,60,65,70,75,80)	15	eg. “Speed 25”	99.1	56
5	Turn Prohibition (No Left turn, No Right Turn, No U Turn)	3	eg. “No Left Turn”	95.8	13
6	Rectangle (SpeedLimit, Left Turn Arrow, Right Turn Arrow, Straight Arrow, Up Arrow, Down Arrow)	6	eg. “Left Turn Arrow”	91.34	49
7	Direction Sign (North, Left, South,West, JCT, TO, End)	7	eg.“North”	93.9	45
8	Center Lane Sign	1	“Center Lane”	99.2	24
9	General Guide Sign (Left, Right, Up, Down, Straight)	5	eg.”Left”	92.6	31
10	Exit Sign	1	“Exit”	95.1	32
11	No Parking Sign	3	“No Parking”	92.7	27
12	Pedestrian Sign	3	“Pedestrian signs”	96.2	41

The experiments conducted for this research demonstrate that the algorithm based on PCA and SVM performed very well. The next task will focus on improving its accuracy through integrating color and texture features being filled into the SVM.

CONCLUSION

A classification methodology based on PCA and SVM for automated sign inventory is proposed in the research. The inputs to the SVM are the feature vectors obtained after a HSV quantization and PCA feature extraction applied in the ROI (Region of Interest) detected in the raw road sign images. Both techniques decrease the redundant information in the road sign images and thus improve the efficiency of the system. SVM model is then trained and tested with these feature vectors. Our preliminary data shows that based on the methodology of SVM integrated with PCA algorithm, the road sign features could be effectively extracted and the road sign types can be classified with promising accuracy. Further work will consider other feature extraction techniques combined with SVM model.

REFERENCE

1. Burges, J.C. A Tutorial on Support Vector Machines for pattern Recognition, Bell Laboratories, Lucent Technologies, 1997.

2. Lalonde, M. and Li, Y., Survey of the State of Art for Sub-Project 2.4, Road Sign Recognition, 1995.

3. Escalera, A., Moreno, L., et al. Road Traffic Sign Detection and Classification. In *IEEE Transactions on Industrial Electronics*, Vol. 44, pp.848-858, 1997.

4. Kellmeyer, D. L., Zwahlen, H. T., Detection of Highway Warning Signs in Natural Video Images Using Color Image Processing and Neural Networks. *IEEE World Congress on Computational Intelligence., International Conference on Neural Networks*, 1994.

5. Madeira, S. R., Bastos, L. C., Sousa, A.M, Sobral, J. F. and Santos, L. P., Automatic Traffic Signs Inventory using a mobile mapping system. *GIS PLANET 2005, International Conference and Exhibition on Geographic Information*, Estoril, Lisboa, Portugal, 2005

6. Nicchiotti, G., Ottaviani, E., Castello, P., and Piccioli, G. “Automatic road sign detection and classification from color image sequences.” In *S. Impedovo, editor, Proc, 7th Int. conf. on Image Analysis and Processing*, pages 623-626. World Scientific, 1994.

7. Tominaga, S. “A color classification method for color images using a uniform color space.” In *IEEE CVPR*, pages 803-807, 1990.

8. Kang, D.S., Griswold, N.C., Kehtarnavaz, N., An invariant traffic sign recognition system based on sequential color processing and geometrical transformation, *Southwest Symposium on Image Analysis and Interpretation*, IEEE, April, 1994.

9. Gao, X.W., Podladchikova, L., Shaposhnikov, D., Hong, K., Shevtsova, N., Recognition of Traffic Signs based on Their Color and Shape Features Extracted Using Human Vision Models. *Journal of Visual Communication and Image Representation,* 2005.

10. Priese, L., Klieber, J., Lakmann, R., Rehrmann, V., Schian, R., New results on traffic sign recognition, *Intelligent Vehicles Symposium*, IEEE, October, 1994.

11. Priese, L., Lakmann, R., Rehrmann, V., Ideogram identification in a real-time traffic sign recognition system, *Intelligent Vehicles Symposium*, IEEE, September, 1995.

12. Priese, L and Rehrmann, V. "On hierarchical color segmentation and applications." In *Proc. CVPR 1993*, pages 633-634,1993.

13. Jiang, G.Y., Choi, T.Y., Robust detection of landmarks in color image based on fuzzy set theory, *Fourth International Conference on Signal Processing*, IEEE, October, 1998.

14. Ghica, R., Lu, S., and Yuan, X. "Recognition of traffic signs using a multilayer neural network." In *Proc. Can Conf. on Electrical and Computer Engineering*, 1994.

15. Liu, X. H. and Ran, B. Vision-Based Stop Sign Detection and Recognition System for Intelligence Vehicle. In *TRB Annual Meeting*, 2001.

16. Kehtarnavaz, N. and Ahmad, A.,Traffic Sign Recognition in Noisy Outdoor Scenes, In *Proceedings of the Intelligent Vehicles '95 Symposium,* pp 460-465, 1995.

17. Ghica, D., Lu, S., and Yuan,X. Recognition of traffic signs by artificial neural network. In *Proceedings of IEEE International Conference on Neural Networks*, Volume 3, pp1444-1449, 1995.

18. Adorni, G., Da´ndrea, V., Destri, G. and Mordoni, M. Shape Searching in Real World Images: a CNN-Based Approach. In *IEEE.Fourth Workshop on Cellular Neural Networks and Their Applications*, 1996.

19. Vapnik V N, The nature of statistical learning theory. New York, Springer, 1995.

20. Wang, K., Hou, Z., Gong, W., SIFT-Based Road Sign Inventory System, *Transportation Research Board Annual Meeting*, Washington D. C., 2007

21. Hotelling, H., "Analysis of a complex of statistical variable into principal componets," *J. Educ. Psysch*., vol. 24,pp. 417-441, 1993.

22. Chang, C. and Lin, J., LIBSVM: a Library for Support Vector Machines, http://www.csie.ntu.edu.tw/~cjlin/libsvm, 2001.

23. Hsu, Chang, C., and Lin, C., A Practical Guide to Support Vector Classification, available at http://www.csie.ntu.edu.tw/~cjlin, last updated July 18, 2007.