Road Sign Classification without Color Information

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Abstract

The robust and general method for the recognition of traffic devices like road signs in traffic scene images is necessary for the creation of Driver Support System. Color may be used as a useful attribute for the decomposition of classification problem into several apriori defined road sign groups/subproblems. In this paper, the colorless method *for the road sign classification is presented working on gray-level images and allowing the same problem decomposition as its color-based counterpart. The method may be used in combination with the color-independent sign detection algorithms. The road sign recognition system then works entirely without the color which may be used as an alternative procedure when the input traffic scene images lacks good color information.*

1. Introduction

The most important goal of the traffic engineering today is improving of the traffic systems safety and increasing of their efficiency. One possible approach is to make the vehicles more intelligent. These, so-called *smart cars* should help the human driver with predicting and solving of dangerous situations in heavy traffic environments. An intelligent vehicle should be equipped with the *Driver Support System* (DSS) which would use various *sensors* to perceive current traffic situation, advanced information *processing unit* for the decision making and some *actuators* for machine-man interaction [10, 5]. Although many various sensors have been already used within DSS the most important one still remains a camera which grabs an image of the traffic scene. The image processing and computer vision methods then naturally play the key role in the DSS design.

Figure 1. Differences between European road signs (sign A12 “Children”)

There exist several types of objects the DSS should recognize like traffic devices, other vehicles and pedestrians. Traffic devices offer the driver information necessary for successful driving. Let us name at least directional information (traffic lanes), current traffic situation (traffic lights), warnings, prohibitions and the navigation data (road signs).

Let us now define the road sign recognition problem :

- The goal is to find and classify road sign boards. In general, these outdoor scenes are acquired from a moving vehicle and therefore suffer from car vibrations and motion blur. Sign boards are often deteriorated by weather conditions and contain dust or scratches.
- Although road signs are defined by international standards large variations can be observed in reality (see examples of European warning signs on figure 1).
- The recognition must be carried out quickly if it should help the human driver - the real time operation is necessary. Moreover, the large number of false alarms (both rejections and acceptations) may have adverse impact to overall system safety.
- No datasets for training or evaluation are freely available because of the commercial nature of the problem. Therefore, the evaluation and comparison of different recognition systems is very difficult.

In the paper just the ideogram based road signs are considered and not the complex information boards.

The first paper on the road sign recognition appeared in Japan in 1984. The subject has then quickly become the field of applied research supported by large companies in the automotive industry. The paper of Lalonde and Li [7] brings the compilation of groups, approaches and results before 1995. The encouraging results are currently reported by groups supported by Daimler-Chrysler concern [15, 4, 18].

Aside from special purpose algorithms for the recognition of particular road sign type (e.g. the stop sign) several more general methods have been published splitting the recognition process in two separated blocks - the sign *detection* and the sign *classification* stages.

The common solution to detect the road signs in the traffic scene image is a color segmentation method. The classification is then usually carried out using some kind of neural network or by the cross-correlation technique [7, 3].

The fast and robust color segmentation of generally illuminated outdoor scenes is a very complicated problem [1, 16]. Perhaps the most advanced segmentation method of Priese *et al.* described in [15] gives promising results but is very computationaly intensive. It still remains an open problem how to segment traffic scenes correctly under adverse illumination (e.g. in twilight or fog).

Another road sign detection approach is the using of the edge information. The recognition system then becomes color-independent. Such solution was presented e.g. by Piccioli *et al.* in [13]. Gray-level and also color images (if available) could be processed in order to find geometrical shapes corresponding to road signs. The cross-correlation method was used for sign classification.

2. The Road Sign Recognition System

The paper describes the classification module of the Road Sign Recognition System (RS^2) being developed at the Faculty of Transportation Sciences, CTU in Prague, since 1995. It employs color-independent sign detection algorithm based on Hierarchical Spatial Feature Matching (HSFM) method of Seitz [17]. In the method, enhanced further by Líbal *et al.* [8], local orientations of image edges and hierarchical templates are used for the shape detection. The input images are processed on several levels of pyramidal structure to achieve scale-change robustness.

The detection algorithm generates a list of regions where some geometrical objects resembling road signs have been found. The list is then passed to the classification module which either labels the regions by sign types or rejects them. It is important to note that the rotation invariance is solved by the template design in the detection block and need not to be managed by the classifier itself.

The RS^2 classification algorithm is designed to be general enough to work with the most of ideogram-based road signs [11, 12]. The basic idea used in the algorithm design is to capitalize the apriori knowledge about the road signs as much as possible.

Road signs are designed to offer their basic meaning (e.g. the warning or prohibition) by the combination of colors and shape. The exact sign type is then specified by the ideogram. Presented classification method exploits the apriori information about road sign grouping for the problem decomposition. Therefore, the classifation algorithm is not one single unit but rather a decision tree having several interesting properties.

The first one is the existence of *partial results*. In the

case of too distant sign valuable ideogram data is often missing. The system then reports at least the coarse meaning (for example prohibition sign).
Secondly, the multi-stage approach allows the system to reject false alarms of the detection layer quickly.
Thirdly, as we classify into smaller number of classes less features is necessary to solve the problem. Moreover, each individual classifier may take advantage of the most descriptive feature set for particular sign group.

3. Colorless Classification Algorithm

Recent version of the classification algorithm used color features within the decomposition procedure which made the classifier the only color-dependent RS^2 module [12]. The purpose of the paper is to show that even gray-level features may be used for the task splitting instead of the color ones. Let us discuss the decomposition strategy on the example of circular road signs.

Four different groups of circular road signs with different basic meanings and color combinations exist (see figure 2). At the beginning, *blue-white*, *red-blue* and *red-white-(black)* signs are split apart in classifier 1. *Blue-white* and *red-blue* signs can be then classified into their terminal classes. Remaining *red-white-(black)* prohibition signs fall into two other groups. Two frequently used *red-white* signs (B1: *Closed to all vehicles* and B2: *Wrong way*) are in the first and several other prohibition signs containing some black ideogram are in the second one. Classifier 4 therefore labels an image as B1, B2 or passes unknown prohibition signs to the last classfier 5.

Each candidate region found by the detection layer and passed to the classifier is preprocessed by cutting the image corners. Two feature types have been used in order to separate above mentioned road sign groups in gray-level images. These are characteristics reflecting the color (or gray) conditions and also basic shape descriptors. Following features were computed on *gray image histogram* :

$$\text{mean} \qquad S_M = \sum_{b=0}^{L-1} bP(b) \qquad (1)$$

$$\text{energy} \qquad S_N = \sum_{b=0}^{L-1} [P(b)]^2 \qquad (2)$$

$$\text{entropy} \qquad S_E = \sum_{b=0}^{L-1} P(b) \log_2[P(b)], \qquad (3)$$

where b denotes particular histogram level, L stands for the number of levels ($L = 256$ for 8-bit images) and $P(b)$ is the estimated probability of b-th level occurrence in the image [14]. Image projections (sums of brightness values in image rows or columns) were also used for computation of *mean*, *energy* and *entropy*. Projections supply valuable spatial distribution of brightness for the sign image. For the suitable shape description several moment invariants have been used. The *unscaled central moment* of order m, n enumerated on the image function $F(j,k)$ is defined as

$$U_U(m,n) = \sum_{j=1}^{J}\sum_{k=1}^{K}[x_k - \bar{x}_k]^m[y_j - \bar{y}_j]^n F(j,k). \qquad (4)$$

Terms $\bar{x}_k$ and $\bar{y}_j$ denote image centroid coordinates. The *normalized unscaled central moment* V of order m, n is then computed as

$$V(m,n) = \frac{U_U(m,n)}{[M(0,0)]^\alpha}, \text{ where } \alpha = \frac{m+n}{2} + 1. \qquad (5)$$

It offers scale-change invariance. These features are used for the computation of Hu's moment invariants h_d of degree $d = 1, ..., 7$ and other useful shape descriptors commonly used in the shape recognition area [14].

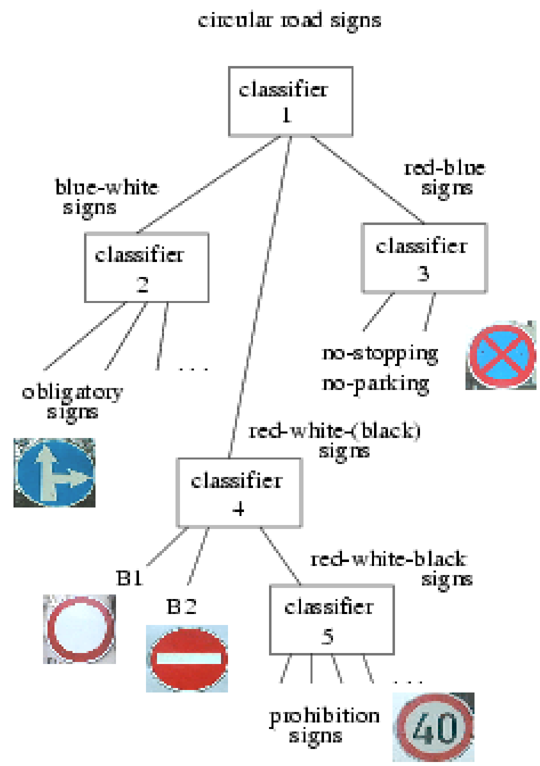

Figure 2. circular road signs classification tree

The classification method used in all experiments is

Figure 3. road signs used in experiments

based on Parzen window classifier with product Laplace kernel. A nonparametric estimate of class conditional densities $f(\mathbf{x}|\omega)$, $\omega = 1, ..., C$ provided by the kernel method is

$$\hat{f}(\mathbf{x}|\omega) = \frac{1}{N_\omega h_\omega^D} \sum_{i=1}^{N_\omega} K\left(\frac{\mathbf{x} - \mathbf{x}_i^\omega}{h_\omega}\right), \qquad (6)$$

where C stands for classes count, N_ω is ω-th class sample count, $\mathbf{x} \in R^D$ denotes the feature vector, $K(\cdot)$ is a kernel function that integrates to one and h_ω is a smoothing parameter [2].

The multivariate product kernel estimate of $f(\mathbf{x}|\omega)$ is then given by equation

$$\hat{f}(\mathbf{x}|\omega) = \frac{1}{N_\omega h_{\omega 1} \dots h_{\omega D}} \sum_{k=1}^{N_\omega} \left\{ \prod_{j=1}^{D} K\left(\frac{x_j - x_{kj}^\omega}{h_{\omega j}}\right) \right\},$$

where x_j is the j-th component of the vector $\mathbf{x}$ and $\mathbf{x}_i^\omega = (x_{i1}^\omega, ..., x_{iD}^\omega)$, $i = 1, ..., N_\omega$. It means that the same univariate kernel K is used in each dimension but with a different smoothing parameter $h_{\omega j}$ for each dimension. The univariate kernel function for Laplace density is defined as

$$f_L(x; \mu, \sigma) = \frac{1}{2\sigma} \exp\left(-\frac{|x - \mu|}{\sigma}\right), \qquad (7)$$
$$\text{where} \quad x \in R, \mu \in R, \sigma \in (0, \infty).$$

The unknown smoothing parameters $h_{\omega 1}, ..., h_{\omega D}$ are estimated using the pseudo-likelihood cross-validation method by the EM algorithm. The detailed description of optimization algorithm can be found in [12].

The reason for using the Laplace kernel instead of the more common Gaussian kernel is the fact that the choice of kernel function is not as important as the proper selection of smoothing parameters [9]. It follows from experiments on road signs data that the optimization of Laplace kernel smoothing converges several times faster compared to the Gaussian one. The differences in classification results of both kernels are, on the other side, negligible.

4. Experiments

The original set of 558 images used in experiments was acquired with digital camera under general illumination conditions. The lighting conditions vary from full sunshine to cloudy twilight. The dataset contains images of both new and old (deteriorated, dusty, dirty) road signs. Additional sign images were obtained by random scaling of original ones. Thus, the experimental dataset contains 1668 images of 18 circular road sign classes. The image size changes between 15 and 150 pixels. Each sample image was transformed from the original RGB color space into gray-level format. The set of 23 gray-level features was used in experiments.

The decision tree consists, in fact, of five separate classifiers working in different feature spaces. To choose the best feature subsets for individual tree nodes the same feature selection method has been employed. For each node the Fisher criterion [6] was computed for all features. These features were then sorted according to criterion values. The performance of classifier working with the n best features was then used to find the best feature subset. The testing scheme is based on rotation method – the dataset is split randomly into training and testing parts. The classifier is trained on the training dataset and tested on the testing one. The procedure is repeated several times and results are averaged.

The results of rotation for all five decision tree nodes are given in tables below. For varying n the mean $\hat{\mu}$ of the error rate percentages and its standard deviation $\hat{\sigma}$ are given. The feature subset size used in final decision tree is typeset in bold face. All experiments were repeated 40 times and training/testing ratio for splitting of the original dataset was 0.8 in all cases. For comparison, the best results of color-based algorithm[12] are also shown for each tree node. Results are again means and standard deviations of error rate percentages [11]. The feature count of used dataset and number of rotations are added too. The color-based experiments were also repeated 40 times.

Classifier 1 : separation of *blue-white*, *red-blue* and *red-white-(black)* sign groups.

dataset : 1668 samples, 3 classes

color-based method : $\hat{\mu}$=0.2%, $\hat{\sigma}$=0.18%, 2 features

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
4	3.88	1.18
8	0.77	0.26
12	0.56	0.13
14	**0.40**	**0.14**
16	0.40	0.12
18	0.43	0.16

Classifier 2 : obligatory road signs

dataset : 444 samples, 9 classes

color-based method : $\hat{\mu}$=3.37%, $\hat{\sigma}$=0.76%, 11 features

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
6	5.57	6.01
8	5.49	7.93
10	5.00	3.68
12	4.70	4.62
14	**3.66**	**3.61**

From the confusion matrix follows that the most of errors occurs between signs with inverse arrows (C4b,C4c, see the figure 3). It may be caused by the fact that the arrow heads are not distinct for small image sizes.

Classifier 3 : *no-stopping*, *no-parking* signs

data : 309 samples, 2 classes

color-based method : $\hat{\mu}$=0.0%, $\hat{\sigma}$=0.0%, 2 features

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
4	1.45	2.61
6	0.60	1.29
8	0.24	0.60
10	**0.00**	**0.00**

No stopping and *No parking* classes are easily separable by features computed on histogram.

Classifier 4 : B1,B2 signs and prohibitions

data : 915 samples, 3 classes

color-based method : $\hat{\mu}$=1.09%, $\hat{\sigma}$=0.98%, 2 features

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
5	3.06	1.86
7	2.73	1.02
9	**1.42**	**0.75**
11	1.33	0.66
13	1.21	0.50
15	1.94	1.35

Classifier 5 : prohibition signs

data : 585 samples, 5 classes

color-based method : $\hat{\mu}$=1.09%, $\hat{\sigma}$=2.12%, 11 features

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
8	6.61	2.65
10	6.09	3.93
12	**1.91**	**1.67**
14	1.74	1.61

Overall performance of the classification tree

For the testing of the decision tree the rotation method was used again. The original dataset (1668 samples, 18 classes) was split into training and testing parts (training/testing ratio 0.8). The best feature subsets found by the method mentioned above were used for training and testing of decision tree nodes. The perfomance of the decision tree after 40 rotation cycles is : $\hat{\mu} = \mathbf{3.17\%}$ and $\hat{\sigma} = \mathbf{0.95\%}$

The results of color-based decision tree after 40 rotation cycles are : $\hat{\mu} = \mathbf{0.97\%}$ and $\hat{\sigma} = \mathbf{0.20\%}$.

Single-classifier approach

For comparison, the results of a single classifier working with all 18 circular sign classes are given here. The complete dataset with 1668 samples, 18 classes and 23 gray-level features was used for its rotation-based testing.

n best features	$\hat{\mu}$ [%]	$\hat{\sigma}$ [%]
6	16.87	3.28
8	12.88	2.87
10	9.22	1.85
12	9.49	1.32
14	6.54	0.98
16	3.68	0.93
18	**3.39**	**0.91**

The best result is somewhat (but not significantly) worse then that of the decision tree.

Discussion

It follows from our experiments that gray-level features computed on histograms, projections and simple spatial moment invariants may be used for the road sign classification with error rate *under four percent*. The best result obtained recently with color-based features is one percent of error.

Two different approaches for the classification of circular road signs have been tested - the decision tree using apriori knowledge about road sign grouping and one single classifier. It appears that the decision tree performs similarly to the single classifier for the gray-level features used in this paper.

On the other hand, the decision tree has several important advantages to the one classifier approach – the *number of features is lower* at individual tree nodes compared to single classifier with the similar performance. The best one-classifier result was reached for 18 features. Probability density estimation is problematical in such high-dimensional spaces as the dataset contains too few samples to fill the feature space. Comparable performance of the decision tree was reached with just 14,14,10,9 and 12 features in its nodes.

Each decision tree node may use the featureset which discriminates corresponding classes in the best way. The feature selection method we used is very simple as it employs just separability of individual features and not of their combinations. More powerful feature selection method will be tested in the future.

For a real road sign recognition system the rejection of false alarms generated by the detection layer is of crucial importance. The decision tree approach allows faster rejection of non-sign regions.

The comparison between gray-level and color-based approach is possible as we have tested the similar decision tree on the same dataset. The color-based method gives comparable results as the gray-level approach but with lower feature counts in all nodes (2,11,2,2 and 11).

Finally, we should stress that the dataset we used for experiments is small and more training samples should be used to allow some general conclusions.

5. Conclusion

In the paper colorless method for classification of circular road signs has been presented in two variants - single classifier and decision tree. The main paper objective was to present the fact that the decomposition of the road sign classification problem may be done *without* the color information. Results are weaker then that of color-based algorithm. Anyway, the colorless approach could have two practical applications. The first one is in the recognition systems independent on color in the sign detection step (such as RS^2). The second possibility is to use this method as an alternative approach for the case of bad illumination conditions.

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