# FALSE ALARM FILTERING IN A VISION TRAFFIC SIGN RECOGNITION SYSTEM

## *An Approach based on AdaBoost and Heterogeneity of Texture*

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Abstract: The high variability of road sign appearance and the variety of different classes have made the recognition of pictograms a high computational load problem in traffic sign detection based on computer vision. In this paper false alarms are reduced significantly by designing a cascade filter based on boosting detectors and a generative classifier based on heterogeneity of texture. The false alarm filter allows us to discard many false positives using a reduced selection of features, which are chosen from a wide set of features. Filtering is defined as a binary problem, where all speed limit signs are grouped together against noisy examples and it is the previous stage to the input of a recognition module based on Support Vector Machines (SVMs). In a traffic sign recognition system, the number of candidate blobs detected is, in general, much higher than the number of traffic signs. As asymmetry is an inherent problem, we apply a different treatment for false negatives (FN) and false positives (FP). The global filter offers high accuracy. It achieves very low false alarm ratio with low computational complexity.

## 1 INTRODUCTION

Traffic sign detection and recognition tasks based on vision systems and artificial techniques arise in a wide range of applications, such as intelligent vehicles that operate automatically, advanced driver assistance systems (ADA), which use the information captured from sensors surrounding the vehicle to assist the driver or automatic traffic sign inventory in order to maintain highway infrastructure periodically, which allows to alert about the lack of visibility of specific traffic signs.

Independently of the application, time optimization is a crucial item in a traffic sign detection system and one of the major problems is the high number of false alarms that the system considers as potential signs even when the number of positive targets in each image is too low. As the computational load depends on the number of samples to analyze, processing time becomes considerable. In this paper we present a false alarm filter integrated in a vision system in order to discard these candidate objects as soon as possible.

There are several approaches to detect traffic signs. Many of them are based on color segmentation using different spaces, such as RGB (de la Escalera et al., 1997) or HSI (Maldonado-Bascón et al., 2007) considering particular colors of the signs present in cluttered scenes. Other alternatives use borders detection, texture detection and genetic algorithms (de la Escalera et al., 2003). More recently (Bahlmann et al., 2005) suggested AdaBoost for detection. With respect to identification module, neuronal networks, (Fang et al., 2003), and support vector machines, (Maldonado-Bascón et al., 2007), have been the recognition techniques most widely used. Specifically, the last one is well known by their excellent generalization properties as it can be demonstrated even when the dataset has a high number of classes. Other approaches are based on the use of Matching Pursuit (MP) (Hsu and Huang, 2001) and Human Vision Models (Gao et al., 2006). Although the input to these classifiers is in most cases the gray level of the pixels in the space domain, other researches conform the underlying vector extracting features, such as histograms (Vicen-Bueno et al., 2005), FFT computed after a complex log-mapping of exterior borders (Hibi, 1996) and wavelets (Hsu and Huang, 2001).

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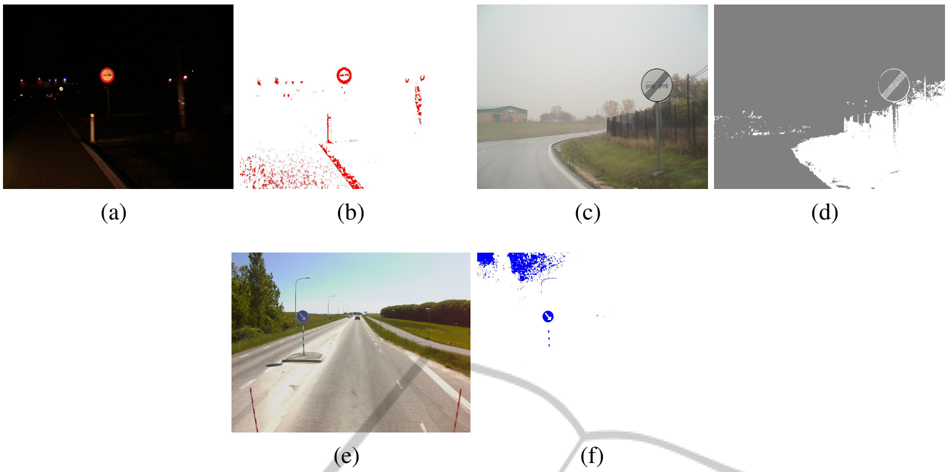


Figure 1: Examples of segmentation processes. (a), (c), (e) Original images; (b) red mask; (d) achromatic mask; (f) blue mask.

## 2 SYSTEM OVERVIEW

An exhaustive description of the traffic sign detection and recognition system (TSDRS) on which this research is based can be found in (Maldonado-Bascón et al., 2007) and (Gil-Jiménez et al., 2008). The system consists of the following steps: segmentation, detection and recognition. Although this work is focused in the improvement of the last stage, it is necessary to make a brief description of the whole system.

### 2.1 Segmentation

The purpose of this stage is to isolate candidate traffic signs from the background of the scene. Color information, specifically HSI space, is considered in our system to extract candidate objects from the input image by thresholding. Major advantage of HSI space is that its color components, Hue and Saturation, are closely related to human perception. In addition, an extra achromatic decomposition similar to the one used in (Liu et al., 2002) is implemented. In Figure 1 some segmentation examples are illustrated, including only the interest masks for each case.

### 2.2 Detection

The detection block aim is the identification of the shape of each candidate blob. Our algorithm compares the signature of the objects under analysis with the theorethical signatures in a discrete set of angles, being defined the signature as the distance from the mass center to the edge of the blob as a function of the angle. The Figure 2 shows the signature of a triangle.

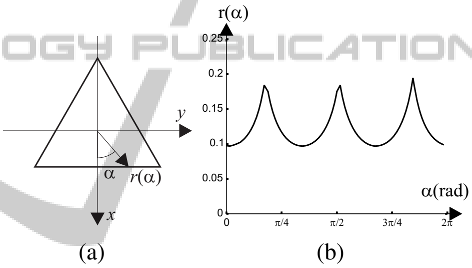


Figure 2: Shape signature of a triangular sign. (a) Reference shape; (b) associated signature.

To make the algorithm invariant to object rotations, comparisons are performed using the absolute value of the FFT of the signature.

### 2.3 Recognition

The purpose of this stage is to identify the information related to the pictogram of candidate traffic signs. This step is implemented by SVM with Gaussian kernel where the input vector is a normalized-size block in gray-scale for each candidate blob. The strategy we follow is one-against-all with a number of classifiers equal to the number of classes that belong to each case to analyze, regarding to color and shape. We must point out that only some pattern vectors of the training set define the decision hyperplane. These pattern vectors are known as support vectors.

# 3 COMPUTATIONAL LOAD

As well as achieving high accuracy, a recognition system should also prevent erroneous identification of non-signs, i.e., limiting the number of false alarms and even when the purpose is not oriented to real time applications (in our case we are concerned about road maintenance tasks), the computation time should be as low as possible. Computational time required to process an image in a TSDRS depends on multiple factors. The most relevant are related to:

1. **Image Properties.** The properties of the images to capture are easily configurable through the acquisition system. Computational load in the segmentation stage is strongly influenced by image size, especially when algorithms work in a pixelwise fashion. We can reduce the image size considering a trade-off between speed and detection probability since small objects in the scene are difficult to detect and identify. Furthermore, in the case of a TSDRS that includes tracking it is crucial to detect the signs since that appear in the first frames of the sequence with small sizes. Other criterion to consider is wether the system works with grayscale or color images. Processing with grayscale images demands lower computational load but color information is lost. With the purpose to reduce the image analysis a possible alternative is to define the area to explore.
2. **Number of Segmentation Algorithms.** As we demonstrate in (Gómez-Moreno et al., 2010) there's not an algorithm robust enough to all difficulties from outdoor environments. For this reason, our TSDRS allows us to work with different algorithms in parallel although their information is highly redundant and the load complexity increases.
3. **Complexity of the Recognition Module.** In a recognition system based on SVMs the number of support vectors grows as the number of classes and training samples do.

In order to find the main bottlenecks and optimize the system to improve its performance, we analyze the computation profile. In Table 1 profiles of the three main stages mentioned are summarized. The rest of processing time is dedicated to other tasks, such as image read/write operations. By a simple inspection, we can observe that computational load of the recognition process is approximately 15 and 46 times higher than the corresponding to the detection stage and segmentation detection stage, respectively. The reason is a consequence of the high number of support vectors to manage in the test phase when a realistic road sign database is considered.

Table 1: Computational load in the three sub-stages of the TSDRS.

| Process | CPU cycles |
|---|---|
| Recognition | 49363 |
| Detection | 3118 |
| Segmentation | 1068 |

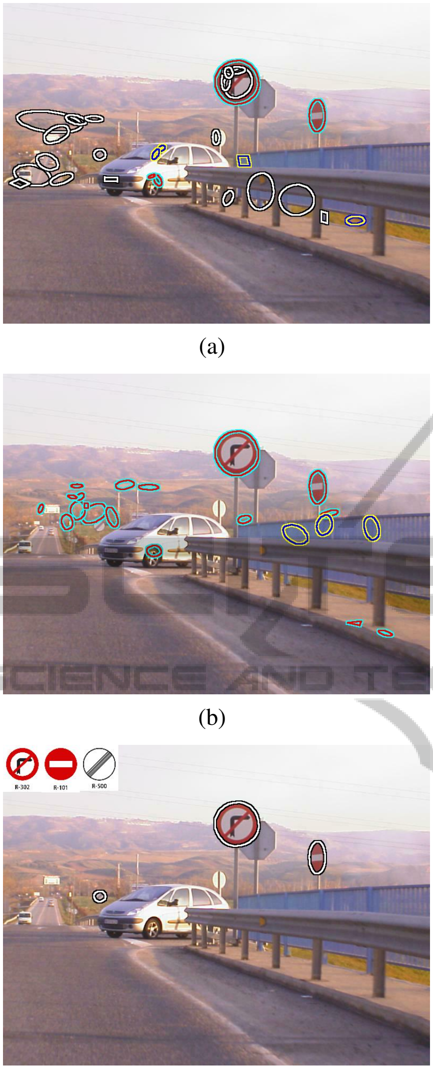
In this way, since the recognition module based on SVMs is executed for every candidate object, computational cost for each frame increases linearly with the number of objects at the input of the recognition stage. Unfortunately, most of theses objects are false positives. So, in Fig.3 we can observe the output detection module for an image, to which we apply two segmentation algorithms. Note that all the detected objects are identified through their corresponding geometric shape. In the recognition stage all false alarms are discarded, but our aim in this research is to reduce the number of objects evaluated in this process due to its computational load.

In this research our proposal is to decrease the number of false positives at the input of the recognition module in order to minimize the computational load. The aim is to implement a false alarm filter using the Viola-Jones detector as a previous step to the recognition module based on SVM and so, reduce the load of the TSDRS.

# 4 FALSE ALARM FILTER

In machine learning community it is well known that more complex classification functions yield lower training errors yet having the risk of poor generalization. If the main consideration is test set error, structural risk minimization provides a formal mechanism to select a classifier with the right balance of complexity and training error. Another significant consideration in classifier design is computational complexity. Since time and error are fundamentally different quantities, no theory can simply select the optimal trade-off. Nevertheless, for many classification functions computation time is directly related to the structural complexity. In this way temporal risk minimization is clearly related to structural risk minimization.

This direct analogy breaks down in situations where the distribution of classes is highly skewed. For example, in our TSDRS there may be dozens of false positives among one or two traffic signs in an image. In these cases we can reach high detection rates and extremely fast classifications. The key insight is



(a)

(b)

(c)

Figure 3: Candidate objects before the recognition stage. (a),(b) Candidate objects represented by their corresponding shapes for each segmentation algorithm. (c) Traffic sign recognition results once detected objects from both algorithms have been integrated.

that while it may be impossible to construct a simple classifier that can achieve a low training/test error, in some cases it is possible to construct a simple classifier with a very low false negative rate. For example, it is relatively simple to construct an extremely fast classifier with a very low false negative rate (i.e. it almost never misses a sign) and a 50 false positive rate. Such a detector should be more accurately called a classification pre-filter: when an image region is labeled non-sign then it can be immediately discarded, but when a region is labeled sign then further classification effort is required. Such pre-filter can be implemented through a cascade of classifiers (see Figure 4), where

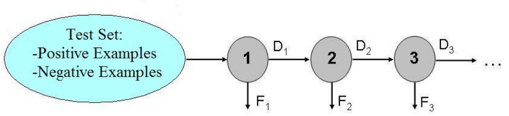


Figure 4: Schematic diagram of a detection cascade. The initial stages eliminates a large number of negative examples with very little processing. After several layers of processing the number of false alarms have been reduced radically.

each classifier follows the AdaBoost algorithm. In the design of such structure, several parameters have to be fixed: maximum false positive rate ($F_{\max}$) of the cascade, minimum detection rate ($D_{\min}$) of the cascade, maximum false positive rate ($f_{i|\max}$) of the $i$th classifier and minimun detection rate ($d_{i|\min}$) of the $i$th classifier. Given a trained cascade of classifiers, the detection and false positive rate are:

$$F = \prod_{i=1}^{K} f_i \tag{1}$$

$$D = \prod_{i=1}^{K} d_i \tag{2}$$

where $K$ is the number of classifiers, $F$ and $D$ are the false positive rate and detection rate of the cascade, respectively, and $f_i$ and $d_i$ are the false positive rate and the detection rate, respectively, of the $i$th classifier.

Even though there are many stages, most are not evaluated for many noisy samples since they are discarded at the first stages. In a cascade, computation time and detection rate of the first stages is critically important to overall performance. In the cascade structure each stage is implemented according to the AdaBoost algorithm due to its low computational complexity in the test phase.

Major extensions of this method have been proposed in two directions: improvement of the algorithm and feature sets.

## 4.1 Dissociated Dipoles

A more general type of features than the Haar-like ones, the dissociated dipoles or sticks have been presented by Balas and Sinha (Balas and Sinha, 2003), which are composed of a pair of rectangular elements, named the excitatory dipole and the inhibitory dipole, respectively (see Fig. 5). As in the case of Haar-like features, the integral image is used to calculate the sum of the pixels inside the rectangular regions and the feature value is equal to the difference between the values of both dipoles normalized by the number of stick pixels.

Taking into consideration color information, we

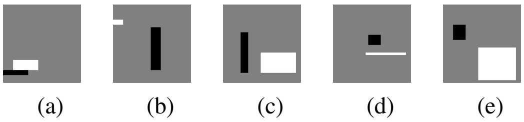


Figure 5: Examples of dissociated dipoles. The white region corresponds to the excitatory dipole whereas the black region corresponds to the inhibitory region.

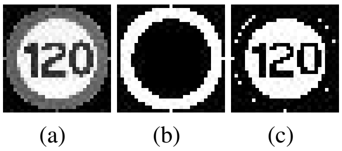


Figure 6: Channels of feature extraction in an example. (a) Luminance channel, (b) Red Channel, (c) White channel.

propose to apply dipoles in different color components. When the dipole is applied to each color channel, the feature represents the average intensity of a specified color component over the region. Specifically, we consider four color channels: red, blue, white and yellow and an additional luminance channel. Previously to the integral image, we extract the color mask in the same way than in segmentation process using HSI for red and blue channels and an achromatic decomposition for white channel. In Fig.6 we can observe the masks corresponding to the luminance and the red and achromatic channels for one example. The blue and yellow masks are not illustrated since all pixels have a zero value.

The contribution of a dissociated dipole for each channel is computed as the difference mentioned above between the excitatory and inhibitory regions:

$$Value = \left(\frac{I_{\text{channel}}}{N_{\text{channel}}}\right)_{\text{exc}} - \left(\frac{I_{\text{channel}}}{N_{\text{channel}}}\right)_{\text{inh}} \quad (3)$$

In the case of the luminance channel, $I_{\text{channel}}$ represents the sum of gray levels in region delimited by the stick, whereas in each color channel represents the number of pixels segmented by this color. $N_{\text{channel}}$ is the number of pixels of the region which are covered by the stick.

With the purpose to make qualitative comparisons between the sticks, we can simplify the expression considering only the sign of the difference. This approach presents luminance normalization as advantage.

## 4.2 Discrete AdaBoost

AdaBoost algorithm finds precise hypotheses by combining several weak classification functions which have moderate precision. AdaBoost is an iterative algorithm that finds, from a feature set, some *weak* but discriminative classification functions and combines them in a *strong* classification function:

$$H = \begin{cases} 1, \sum_{t=1}^{T} \alpha_t h_t \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t = S, \\ 0, \text{otherwise} \end{cases} \quad (4)$$

where $H$ and $h_t$ are the *strong* and *weak* classification functions, respectively, and $\alpha_t$ is a weight coefficient for each $h_t$. Different variants of boosting are developed: discrete AdaBoost, real AdaBoost, gentle AdaBoost, and so forth. However, we use the first one.

Each *weak* classifier is defined for a feature $j$ as a binary response:

$$h_t = \begin{cases} 1, \text{if} p_j f_j < p_j \theta_j \\ 0, \text{otherwise} \end{cases} \quad (5)$$

where $f_j$ is the value of the feature $j$, which is given by the contribution of a dipole as it is mentioned above, $\theta_j$ is the threshold and $p_j$ is the parity. For each feature $j$, AdaBoost determines an optimal threshold $\theta_j$ for which the classification error on training database (with positive and negative examples) is minimized. The weight coefficient for each $h_t$ is computed as:

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - e_t}{e_t}\right) \quad (6)$$

where $e_t$ is the sum of the weigths associated to the samples classified wrongly.

## 4.3 Assymetric Recognition

Asymmetry is an inherent problem in recognition systems where the number of positive targets is too low with respect to negative patterns. That is, to achieve a high detection rate, the cost of missing a target should be higher than that of a false positive. Cost-sensitive learning is a suitable way for solving such problems. However, most cost-sensitive extensions of AdaBoost are realized by heuristically modifying the weights and confidence parameters of the discrete AdaBoost. Thus, there should be different treatment for false negatives (FN) and false positives (FP), that is, FN samples are penalized more than FP samples. Since AdaBoost aims at minimizing the bound of classification error which treats FP and FN equally, the symmetric AdaBoost algorithm is not optimal for object detection tasks. To deal with the class imbalance problem in classification, various asymmetric extensions of AdaBoost have been proposed in the literature. Most of them directly modify the weights and confidence parameters of discrete AdaBoost without clarifying the relations to the loss minimization

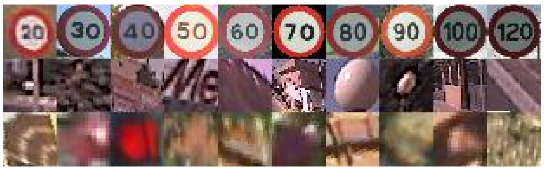


Figure 7: Examples of the benchmark data set. First row includes positive samples whereas second and third row include noisy ones.

of AdaBoost. AdaCost (Fan et al., 1999) proposed by Fan adopts an approach to make AdaBoost cost-sensitive. They incorporated a cost adjustment function $\beta_\delta(i)$ into the weight updating rule and the computation of $\delta_t$. The weight updating formula was modified into

$$D_{t+1}(i) = \frac{D_t(i)\exp\left(-\alpha_t y_i h_t(x_i)\beta_\delta(i)\right)}{Z_t} \tag{7}$$

where $\alpha_t$ is computed as:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1+r_t}{1-r_t}\right) \tag{8}$$

and $r_t$ is

$$r_t = \sum_i D_t(i)\, y_i h_t(x_i)\, \beta_\delta(i) \tag{9}$$

$\beta$=+1 if the output of the classifier is right and $\beta$=-1 otherwise. Finally,

$$\beta_{+1}(i) = -0.5C_i + 0.5 \tag{10}$$

and

$$\beta_{-1}(i) = 0.5C_i + 0.5 \tag{11}$$

The parameter $C_i$ is the cost factor assigned to the $i$-th sample and is restricted to the interval [0 1].

## 4.4 Results

The Recognition and Multi-sensorial analysis group (GRAM) at the Universidad de Alcalá has collected a complete database of Spanish traffic signs. All the samples have been extracted from images acquired by different video-cameras under variable lighting conditions. The stored patterns are 31×31 pixels gray level with homogeneous background for no-interest pixels. So, the number of significative components is 961 for rectangular signs while in circular signs is reduced to 709 and for for triangular signs to 511. Some examples are shown in Figure 7.

Without loss of generality, in this research we are concerned about the speed limit signs. The benchmark data set is subdivided into three groups: training, validation and test set. From a total set of 872 positive samples and 3475 negative samples, 50% of them are chosen randomly as training set, 25% for the validation set and the remaining 25% forming the test set. Negative samples have been previously taken randomly from arbitrary images. The validation set is used to tune the strong classifier decision thresholds in order to reach the minimum acceptable correct detection rate and the maximum acceptable false-alarm rate during cascade training.

In the final detector the selected values for false positive rate and detection rate of each strong classifier are, respectively, fixed to $f_{i|\max} = 0.9 \cdot f_{i-1|\max}$ and $d_{i|\min} = 0.994 \cdot f_{i-1|\min}$. Moreover, the false positive rate and detection rate of the cascade are fixed to $F$=0.05 and $D$=0.9. The structure of the final detector is a 11 layer cascade of classifiers with a total of 28 features. In Table 2 is summarized the distribution of features among the different stages. The filter achieves a detection rate of 98.58% (3 positive samples of 211 were considered false negatives) and a false positive rate of 5.30% (822 negative samples of 868 were discarded).

In the case of AdaCost boosting, using the same parameters for the cascade structure, the detector we obtained has 6 layers with a total de 28 features. In Table 3 is summarized the distribution of features among the different stages. The filter achieves a detection rate of 98.10% and a false positive rate of 4.15%.

Anyway, from the Figure 7, we can observe that pictograms of signs are well defined. We can take advantage of this fact binarizing the samples using Otsu's method, which chooses a global threshold to minimize the intraclass variance of the thresholded black and white pixels. In Figure 8 are illustrated the samples of Fig 7 after thresholding. For each binarized image we can quantify the heterogeneity of texture computing for every pixel of coordinates ($x$,$y$) the number the pixels in 8-neighboring that present different level respect to it. The value is normalizazed with respect to the total number of pixels that constitute the object.

Normalized mean value of heterogeneity is shown by the solid line in Figure 9, whereas drifts (maximun and minimun) are shown by the dashed lines for the different classes. The last label ($Index = 10$) corresponds to the noisy class. Note that the distribution shows a higher disparity of values for noisy samples (class 10) and it may be discriminant enough for many cases. Thus, only those candidate objects that present a heterogeneity lower than $\theta_1 = 0.75$ and higher than $\theta_2 > 1.80$ will be analyzed by the cascade filter. In fact, 411 negative samples of the 868 (47.35%) that conform the negative test set were discarded using

Table 2: Structure, detection rates and false alarm rates of the filter, which includes 11 boosting layers.

| | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | L10 | L11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| No.Features | 3 | 2 | 2 | 2 | 2 | 4 | 2 | 2 | 3 | 3 | 3 |
| Detection Rate | 99.0% | 99.0% | 99.0% | 98.5% | 98.5% | 98.5% | 98.5% | 98.5% | 98.5% | 98.5% | 98.5% |
| FA Rate | 46.7% | 31.2% | 26.2% | 21.3% | 19.1% | 16.9% | 14.0% | 11.0% | 8.9% | 7.2% | 5.3% |

Table 3: Structure, detection rates and false alarm rates of the filter based on AdaCost boosting, which includes 6 stages.

| | L1 | L2 | L3 | L4 | L5 | L6 |
|---|---|---|---|---|---|---|
| No.Features | 7 | 2 | 5 | 10 | 3 | 1 |
| Detection Rate | 100% | 100% | 99.5% | 99.5% | 98.1% | 98.1% |
| FA Rate | 56.3% | 25.9% | 11.8% | 8.7% | 6.5% | 4.1% |

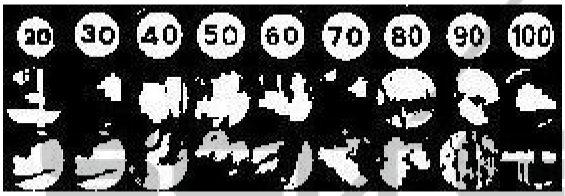


Figure 8: Binarized samples of the benchmark data set using Otsu's method.

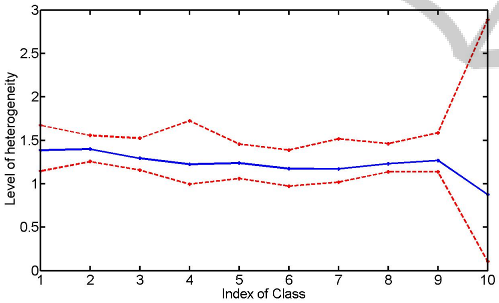


Figure 9: Illustration of the response of heterogeneity of texture for different classes. The solid graph represents the mean value whereas the dashed ones depict the minimum and maximum values. The distribution shows a higher disparity of values for noisy samples (class 10) than for the rest.

this prerequisite. If we integrate this condition in the cascade filter detection based on AdaCost, the filter maintains a detection rate of 98.10% but the false positive rate is decreased until 2.65%. Note than in this case, almost half of noisy examples are discarded directly by the condition of heterogeneity of texture before filtering. Furthermore, the false alarm ratio is improved due to the heterogeneity texture.

Although cascades of boosted ensembles exhibit real-time performance, training time ranges from days to weeks. The factors that affect the training time are the amount of training samples and feature-set size that depends on the actual image dimensions of training samples. The traditional training approach has a run-time of $O(N \cdot T \cdot \log(N))$, where $N$ represents the number of samples and $T$ is the number of features. In our case, we work with a Sun Java WorkStation and the training requires approximately 12 hours of computation for 1600 features.

## 5 CONCLUSIONS

In this paper we present a false alarm filter based on a cascade of boosted classifiers. The filter is integrated in a vision system to detect and recognize traffic signs. In this application the number of positive targets is too low with respect to negative patterns and the computational load of recognition task depends directly on the number of samples to identify. In order to decrease the number of candidate signs to be recognized, the filter has the capacity of discard many false positives with very low operations using the structure of Viola-Jones. One of the main goals of this filter is to include a first discriminant classifier based on a measurement of heterogeneity texture. By combining both techniques, the system achieves a very low false alarm rate with low computational load.

Since in this work, we are concerned about speed limit signs, our future work will be devoted to implement this approach with the whole set of traffic sign set. Furthermore, the enormous time that Viola-Jones algorithm demands in training process, makes it an open item to research.

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