

# Blur-invariant Traffic Sign Recognition Using Compact Local Phase Quantization

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**Abstract**—Traffic signs are characterized by a wide variability in their visual appearance in real-world environments. For example, changes in illumination, varying weather conditions, blurring and partial occlusions impact the perception of road signs. One of the principal causes for traffic image quality degradation is blur. This is frequently due to car motion, camera out of focus, low resolution and atmospheric turbulence. In this paper, we employ a new feature extraction method named Compact Local Phase Quantization (CLPQ) for blur insensitive traffic sign recognition. Various local descriptors such as HOG, LBP are investigated and LPQ shows a high robustness to blur. LPQ features are extracted from phase information of local regions of the traffic signs, this produces a large dimension feature vector which is not practical for real-time application. Minimum-redundancy Maximum-relevance (mRMR) feature selection method is employed to select the most discriminative and non-redundant features. Experimental results show the effectiveness of combining local phase quantization descriptor and mRMR feature selection. The proposed method achieved 98.6% average recognition accuracy on the German traffic sign recognition benchmark (GTSRB) database.

## I. INTRODUCTION

Automatic traffic sign recognition is an important part for an advanced driver assistant system [1], [2], [3]. Traffic signs can increase driving safety by informing the driver about speed limit signs, warning him against possible dangers such as slippery roads, imminent road works or pedestrian crossings. Their bright colours and simplified pictogram make them easily comprehensible and perceivable. However, due to difficult out-door conditions, designing an automatic recognition system for road signs is still a challenging problem.

Traffic signs are characterized by a wide variability in their visual appearance in real-world environments. For example changes in illumination, varying weather conditions, blurring and partial occlusions impact the perception of road signs. One of the principal causes for traffic sign image quality degradation is blur. This is frequently due to camera low resolution, car motion, out of focus or atmospheric turbulence. Recognizing signs subject to arising perturbations and changes in image acquisition process is very challenging, which is often increase the interclass variabilities. In this paper, we propose a compact representation for traffic sign image that is robust to blur.

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Generally most distortion types are very difficult or expensive to cancel it, and the restored image often has rarely employed. Therefore, recent works particularly seek to generate image features that are invariant to selected aspects of image distortions. Humans are capable of recognizing the large variety of existing road signs in most situations with near-perfect accuracy. However, this do not apply to real world driving, where rich context information and multiple views of a single traffic sign are available.

Despite the large research efforts towards image descriptors robust to the aforementioned disturbances [2], the problems caused by blur often present in real-world traffic sign recognition has been overlooked. Blur in traffic signs may be caused by many factors such as car motion, camera exposure, low resolution image, camera out-of-focus, or low quality of the imaging device. There are several video cameras which can correct blurring effect, however this correction is not efficient to deal with large blurring effects caused by car motion.

In this paper, we address the challenges caused by blurring using a recently proposed blur tolerant feature extraction method called Local Phase Quantization (LPQ) [4]. LPQ features are used previously to describe dynamic textures [5], and later used for blur insensitive face recognition [6]. In addition, the performance of various state-of-the-art local descriptors such as HOG [7] and LBP [8] are investigated against a set of artificially generated blurred images, LPQ shows a high robustness to blur. However, LPQ features are extracted using phase information of local regions of the input image and these features exhibit high dimensionality. In order to reduce the dimension of LPQ vector, mutual information criterion based on Minimum-redundancy Maximum-relevance (mRMR) feature selection method [9] is employed to select the most discriminant and non-redundant features. Not only this selection leads to compact the representation of feature vector but also it increases the recognition accuracy.

This paper is organized as follows, section II describes the works related to the proposed method, and section III explains the details of the proposed traffic sign recognition system. Section IV shows the experimental set-up and results using both naturally blurred images and artificially blurred images. Finally, conclusions and future works are described in section V.

## II. RELATED WORK

Recognition of traffic signs has been a challenging problem for many years and is an important task for the intelligent vehicles. Vision-based driver assistance attracted

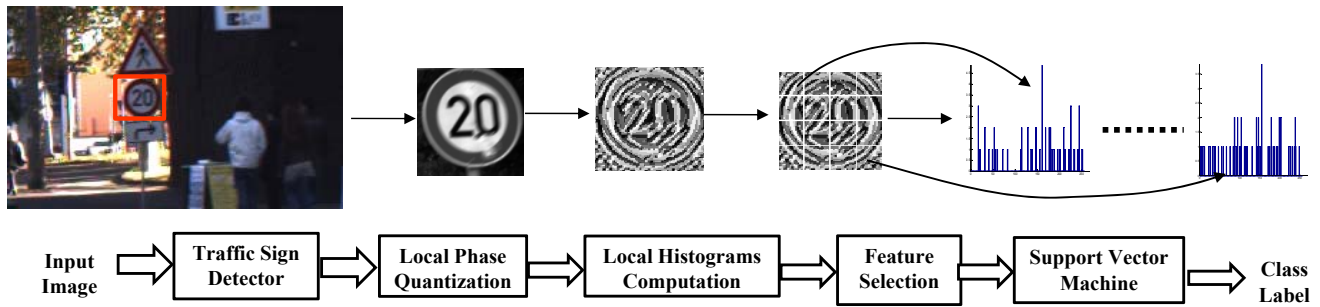


Fig. 1. Overview of the Proposed Road Sign Recognition System

many researchers. There are many feature descriptors used to describe the salient features of traffic signs. Feature descriptor can be categorized into three categories, neural network based features, template-based features and edge-based features. The proposed LPQ features can be considered as an example of edge-based features due to its employment of local phase information.

Zheng et al. [10] proposed a real time traffic sign detection, recognition and tracking system using camera mounted on a moving vehicle. In their work, the detected candidate signs are passed to a template matching stage to determine the content of the sign. Binary robust invariant scalable keypoints (BRISK) features are used in the feature extraction stage which is scale and rotation invariant. The two steps of BRISK method are scale-space keypoints detection and binary bit-string descriptor extraction. Although the method is scale and rotation invariant, the recognition rate highly depends on the quality of keypoint detection which will be affected by noise, blur and other atmospheric disturbance.

Sermant and Lecun [11] employed a multi-scale convolutional neural network (CNN) which is a biologically inspired multilayer feed-forward network. The network learns hierarchies of invariant features. They modified the traditional CNN with multi-scale features extracted from the first and second stage of the network. Although CNN produce excellent results for recognition, its large amount of parameters which should be tuned carefully make it not practical for many applications.

Ciresan et al. [12] also use a committee of multi-layer perceptron (MLP) neural networks and Convolutional neural network to learn traffic sign features in a supervised way. MLP trained on Hue colour features and CNN fed with raw pixel intensities. They used different preprocessing techniques to normalize the data and to increase the contrast of the images. Moreover, grayscale and colour images are used in their experiments. Their results show that adding colour information in the decision-level classification improve the results.

Zaklouta et al. [13], [14] employed histogram of gradient (HOG) to extract traffic sign features. They used random forest classifier for recognition. HOG-based features are originally used for solving human detection problem and so they apply it for sign recognition. However, HOG features

are not robust to changes in blurring.

Ruta et al. [15] addressed the problem of traffic sign recognition using matching between discrete-colour detected image of the observed sign with model images. The features used in their work comes mainly by learning a class-specific sets of discriminative local regions. They introduced a so-called colour distance transform that enables robust distance-colour comparisons. A novel feature selection algorithm is also introduced which extracts a small number of critical local image regions for each sign. Although their method is fast and do not require any training, its robustness against various conditions such as lighting, blurring is not tested.

Greenhalph et al. [16] proposed a real time traffic sign detection, recognition and tracking system. At first, candidate regions are detected using a maximally stable extremal regions (MSERs). Recognition is based on a cascade of support vector machine (SVM) classifiers that were trained using HOG features. Instead of using real data for training, they generate a lot of synthetic training images from traffic sign template images. The performance of their proposed system depends on the accuracy of the shape classifier which used to decide the shape of traffic sign before recognizing it.

### III. PROPOSED SYSTEM FOR TRAFFIC SIGN RECOGNITION

The proposed system for traffic sign recognition contains the following steps: first, the traffic sign region is detected using adaptive learning method based on online gathering of training samples from in-vehicle camera image sequences [17]. Then the detected traffic sign is labelled using local phase quantization method which is blur insensitive image descriptor, the labelled image is divided into non-overlapping rectangular regions of equal size and a histogram of the labels in local regions is computed independently within each region. The histograms from different regions are concatenated to build a global descriptor of the sign image.

The high dimensionality of the feature vector make it not suitable for real-time application, moreover most of these features are redundant. A feature selection method based on the mutual information between features and class labels and among features themselves is employed to select the most relevance and non-redundant features [9]. In the training stage, selected features extracted from different training

images of different categories are used to train the support vector machine classifier [18]. In order to identify the input test sign, the trained classifier is employed on the selected features. The overview of the system is shown in Fig. 1

The local phase quantization operator was originally proposed by Ojansivu and Heikkila for dynamic texture description [4]. The operator was shown to be robust to blur and outperformed the local binary pattern operator [6] in texture classification. We propose to employ this method as a robust feature descriptor for traffic signs.

#### A. Local Phase Quantization

The spatial blurring can be modelled as a convolution between image intensity and a point spread function (PSF). In the frequency domain, this leads to a multiplication  $G = F \times H$ , where  $G$ ,  $F$  and  $H$  are the Fourier transforms of the blurred image, the original image and PSF respectively. The phase of the blurred spectrum image can be also expressed as a sum of the two phase of original and PSF i.e.  $\angle G = \angle F + \angle H$

If the PSF is assumed to be a centrally symmetric, the transform  $H$  becomes real valued and the phase angle  $\angle H$  must be equal to 0 or  $\pi$ . Furthermore, the shape of  $H$  for a regular PSF is close to a Gaussian or a sinc-function, that's make at least the low frequency values of  $H$  to be positive. At these frequencies,  $\angle H = 0$  causes  $\angle F$  to be a blur invariant descriptor. This phenomenon is the basis of the local phase quantization (LPQ) method described in the following.

In LPQ, the phase is examined in local  $M \times M$  neighbourhood  $N_x$  at each pixel position  $x$  of the image  $f(x)$ . These local spectra are computed using a short-time Fourier transform defined by.

$$F(u, x) = \sum_{y \in N_x} f(x - y) e^{-j2\pi u^T y} \quad (1)$$

The transform in Eq. (1) is efficiently evaluated for all pixel positions  $x \in \{x_1, x_2, \dots, x_N\}$  using simply 1-D convolutions for the rows and columns successively. The local Fourier coefficients are computed at four frequency points  $u_1 = [a, 0]^T$ ,  $u_2 = [0, a]^T$ ,  $u_3 = [a, a]^T$ , and  $u_4 = [a, -a]^T$ , where  $a$  is a sufficiently small scalar to satisfy  $H(u_i) > 0$ . For each pixel position this result in a vector, where the value of  $a = 1/W$ , and  $W$  is the size of local filter. The value of  $W$  used in this work is 7 pixels. By increasing this value the tolerance of the descriptor for large blurring is increased.

The phase information in the Fourier coefficients of Eq. (2) is recorded by observing the signs of the real and imaginary parts of each component in  $F_x$ . This is done by using a simple scalar quantizer in Eq. (3).

$$\mathbf{F}_x = [F(u_1, x), F(u_2, x), F(u_3, x), F(u_4, x)] \quad (2)$$

$$q_j(x) = \begin{cases} 1 & \text{if } \text{Re}\{F(u_j, x)\} \geq 0 \\ 0 & \text{otherwise} \end{cases}, \quad (3)$$

where  $g_j(x)$  is the  $j^{\text{th}}$  component of the vector  $G_x = [\text{Re}\{\mathbf{F}_x\}, \text{Im}\{\mathbf{F}_x\}]$ . The resulting eight binary coefficients

$q_j(x)$  are represented as integer values between 0–255 using binary coding

$$f_{LPQ}(x) = \sum_{j=1}^8 q_j(x) 2^{j-1}. \quad (4)$$

As a result, we get the label image  $f_{LPQ}$  whose values are the blur invariant LPQ labels.

#### B. Feature Selection using Minimum-redundancy Maximum-relevance Criteria

Since the resulting dimension of the LPQ feature vector extracted from an image is large. i.e., if the input image is divided into  $5 \times 5$  blocks with 256 values for each local histogram, the dimension of the feature vector becomes  $256 \times 25 = 6400$ . In order to reduce the feature dimensions, features can be selected in many different ways. One scheme is to select features by using statistical analysis of histogram bins [19]. Although this method is simple, the redundancy between features still exist. In this paper, we employ a criteria based on mutual information between features themselves and between features and class labels [9]. Features can be selected to be mutually far away from each other while still having "high" correlation to the classification variable. This scheme, termed as Minimum Redundancy Maximum Relevance (mRMR) [9] selection has been found to be more powerful than the maximum relevance selection. Mutual information is employed as a measure of relevance feature vector. The mutual information  $I$  of two variable  $x$  and  $y$  is defined based on their joint probabilistic distribution  $p(x, y)$  and the respective marginal probabilities  $p(x)$  and  $p(y)$

$$I(x, y) = \sum_{i,j} p(x_i, y_j) \log \frac{p(x_i, y_j)}{p(x_i)p(y_j)} \quad (5)$$

The key idea of minimum redundancy is to select the feature vectors such that they are mutually maximally dissimilar. Minimal redundancy will make the feature set a better representation of the entire data set. Let  $S$  denote the subset of features that we are seeking. The minimum redundancy condition is

$$\min W_I, W_I = \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i, f_j) \quad (6)$$

where  $I(f_i, f_j)$  is the mutual information between  $f_i$  and  $f_j$  which is calculated using Eq. (5). and  $|S|$  is the number of features in  $S$ .

To measure the level of discriminant powers of features when they are differentially expressed for different targeted classes, the mutual information  $I(C, f_i)$  is computed between features and targeted classes  $C = C_1, C_2, \dots, C_K$  using Eq. (5). Thus  $I(C, f_i)$  quantifies the relevance of  $f_i$  for the classification task. The maximum relevance condition maximize the total relevance of all features in  $S$ .

$$\max V_I, V_I = \frac{1}{|S|} \sum_{f_i \in S} I(C, f_i) \quad (7)$$



Fig. 2. Selected Features using minimum-redundancy maximum-relevance for various sign categories

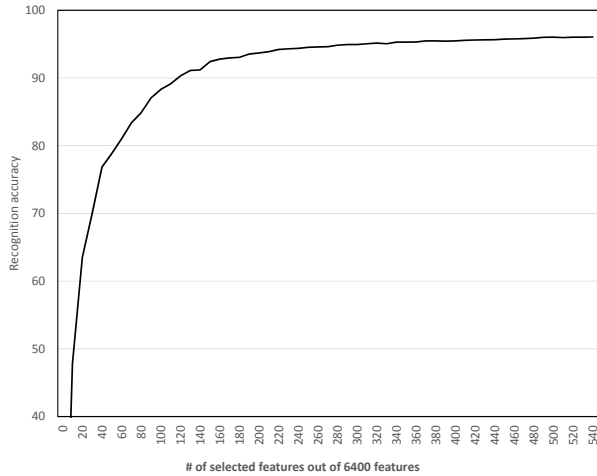


Fig. 3. Recognition accuracy for all images using different numbers of features

The minimum redundancy, maximum relevance feature set is obtained by optimizing the condition in Eqs. (6) and (7) simultaneously. Optimization of these two conditions require combining them into a single criterion function as follows:

$$\max (V_I - W_I) \quad (8)$$

### C. Category Specific Feature Selection

In order to optimize the performance of the system and as the discriminant features differ from one traffic sign category to another. The discriminant features are selected separately for each traffic sign category using mRMR method. i.e. selected features for speed signs are different than features selected for danger signs. Fig. 2 shows the results of selected features from different traffic sign categories. The results reveal that the interior part of the traffic signs is the most discriminative compared with the outside borders, this result is also consistent with other results in [13]. Fig. 3 shows the performance of changing the number of selected features in the recognition accuracy using all dataset in GTSRB. This results reveals that the accuracy for selecting 200 features only from the 6400 features (around 3% of the total features) give 94% accuracy, and the increase in the accuracy by adding more features does not significantly change the accuracy.

## IV. EXPERIMENTAL RESULTS

The efficiency of the proposed system for traffic sign recognition was tested using German Traffic Sign Recognition (GTSRB) dataset [20], which is publicly available.

### A. German Traffic Sign Recognition Benchmark

The GTSRB data set containing 43 classes, the original color images contain one traffic sign each, with a border of 10% around the sign. The traffic signs vary in size from  $15 \times 15$  to  $250 \times 250$  pixels and are not necessarily square. The dataset were extracted from 1-second video sequences i.e. each real world instance yields 30 samples with usually increasing resolution as the camera is approaching the sign. The training set contains 26,640 images while the test set contains 12,569 images.

In all experiments, we crop all images to remove background pixels, then the cropped image converted to grayscale and scaled to fixed size of  $26 \times 26$  pixels. The images are divided into 6 categories for selecting category-specific features and for training a category specific support vector machine classifier. Only 400 features out from the 6400 features are selected using mRMR algorithm to represent input traffic sign image, this low number of features helps to reduce the computation cost and storage requirement of the system. All training images from each category are used to train category-specific multi-class SVM classifier using LIBSVM [21] library. Example of images from all the 43 classes are shown in Fig. 4. In the same manner as the work of [16], a shape classifier is trained to classify signs according to each subset. The shape classifier utilize a subset of selected features from LPQ features, the accuracy of the shape classifier using 400 features was 99.3%.

### B. Recognition using LPQ and SVM classifier for Artificially blurred images

In this experiment, the performance of the LPQ-based system was tested on images blurred artificially. We test two different blurring effects, the first one is the Gaussian blur and the other one is motion blur. All test images in the GTSRB were artificially blurred by convolving them with a Gaussian blur mask has the same size of the input image and with  $\sigma = \{0, 0.25, \dots, 2\}$ . These blurred images were then used for testing the proposed system. Example images blurred artificially from the GTSRB are shown in Fig. 5. The same procedure is repeated for a horizontal motion blur filter with length varies from  $\{0, 1, \dots, 8\}$  pixels.

To compare the robustness of LPQ against different local feature descriptors. The recognition rates for LPQ, LBP [8], and HOG [7] features are plotted in Fig. 6 for Gaussian blurred images. As it can be seen from the results, LPQ produces better results than LBP and HOG even with no blur. The LBP descriptor tolerates slight blur very well but as blur increases from  $\sigma = 1$ , the recognition rate drops rapidly. At  $\sigma = 1.4$ , the recognition rate is 70% for LBP and 63% for HOG and 90% for LPQ. Local phase quantization tolerates blurring much better than LBP and HOG. The recognition rate decrease slightly faster after  $\sigma = 1.4$ , but even at  $\sigma = 2.0$  the recognition rate is still 65%, which is higher than those of LBP or HOG features.

Similarly, the recognition rates for LPQ, LBP, and HOG features are plotted in Fig. 7 for motion blurred images. As it can be seen from the results, LPQ again produces better



Fig. 4. Samples of the 43 classes of the traffic Signs from GTSRB Dataset divided into 6 subsets

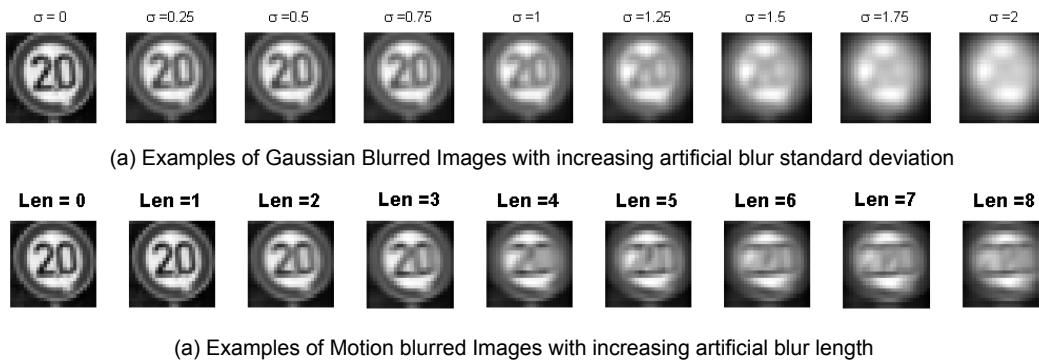


Fig. 5. Samples of Artificially blurred signs using Gaussian blur mask at different  $\sigma$  and various horizontal motion blur mask

results than LBP and HOG. After  $Len = 6$  pixels, the recognition rate of LBP outperformed local phase quantization because of the small window size used to calculate local phases, which is not sufficient to handle large blur variation. To handle such kind of large blurring, the window size of the filter should be adaptively changed according to the size of blurring.

### C. Comparisons with other state-of-the-art Methods

We compared the proposed method with other state-of-the-art algorithms such as committee of CNNs [12], multi-scale CNN [11], random forests [13] and HOG-based LDA [3]. The traffic signs are divided into 6 groups of similar traffic sign categories, as shown in Fig. 4. For each subset, a multi-class SVM classifier has been trained using a specific selected features obtained from mRMR algorithm. Results obtained from these experiments are shown in Fig. 8, the results are compared with other state-of-the-art methods. The average accuracy of the proposed system using all subset images was 98.6%. The proposed method does not require any training which make it more advantageous compared with CNN based. Only 174 images are misclassified and they are shown in Fig. 9. Most of the misclassified patterns have defects in the inside drawings which make it confused with other classes. Additionally, the extreme bad illumination

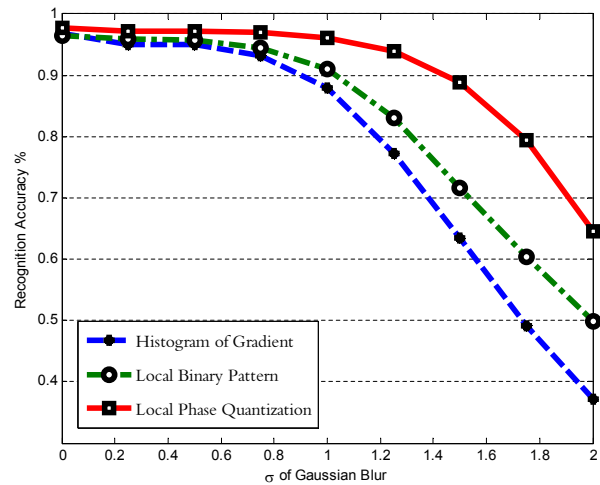


Fig. 6. Recognition rates on GTSRB images with increasing Gaussian blur

condition of the images make it less discriminative and hence becomes high probable to be misclassified. The accuracy of recognizing speed limit signs reach 99% which is comparable with the best achieved one. The danger signs which have triangular shape gave the worst results compared with other traffic sign categories. Since triangular shape sign have

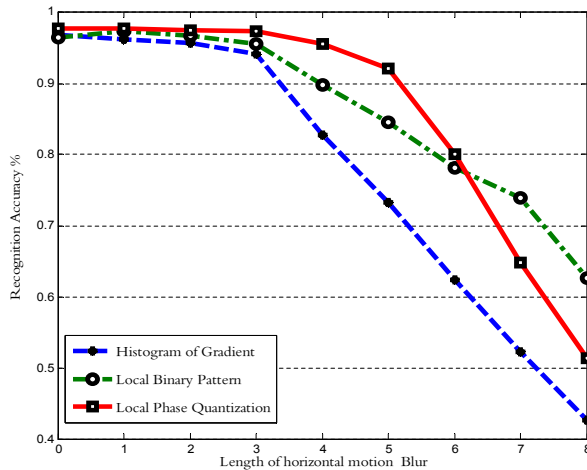


Fig. 7. Recognition rates on GTSRB images with increasing horizontal motion blur

background patches more than other signs, these patches considered as a noise and this make feature vector noisy. Although the proposed method is not the best, it is the only method which are blur invariant and computational inexpensive compared with other methods. because of its direct computation of feature vector without any requirement for training step.

## V. CONCLUSIONS

In this paper, we proposed a new traffic sign recognition system based on compact version of Local phase quantization as a blur invariant features. Most of the previously proposed methods in traffic sign recognition ignoring this problem. The LPQ features is experimentally proved to be very efficient to recognize various kinds of blurring such as Gaussian and motion blur.

The comparisons of LPQ with other local features such as local binary pattern (LBP) and histogram of gradient orientation (HOG) show that LPQ not only the most blur insensitive but also it is the most discriminative. Experimental results show that a few number of features can be used to achieve high accuracy. The combination of local phase quantization, mRMR feature selection method and support vector machine gives a comparable results with other state-of-the-art methods. The recognition rate can be further improved if we add colour information as a complementary feature for LPQ.

## VI. ACKNOWLEDGEMENTS

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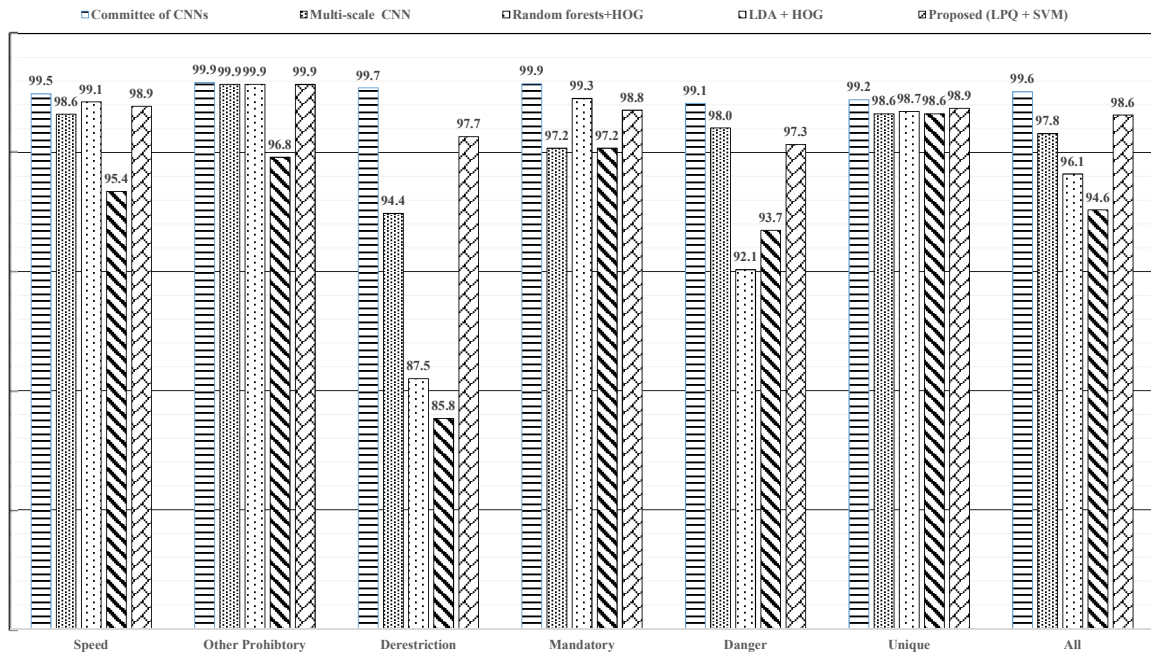


Fig. 8. Comparison of different state-of-the-art algorithms for recognizing GTSRB subsets

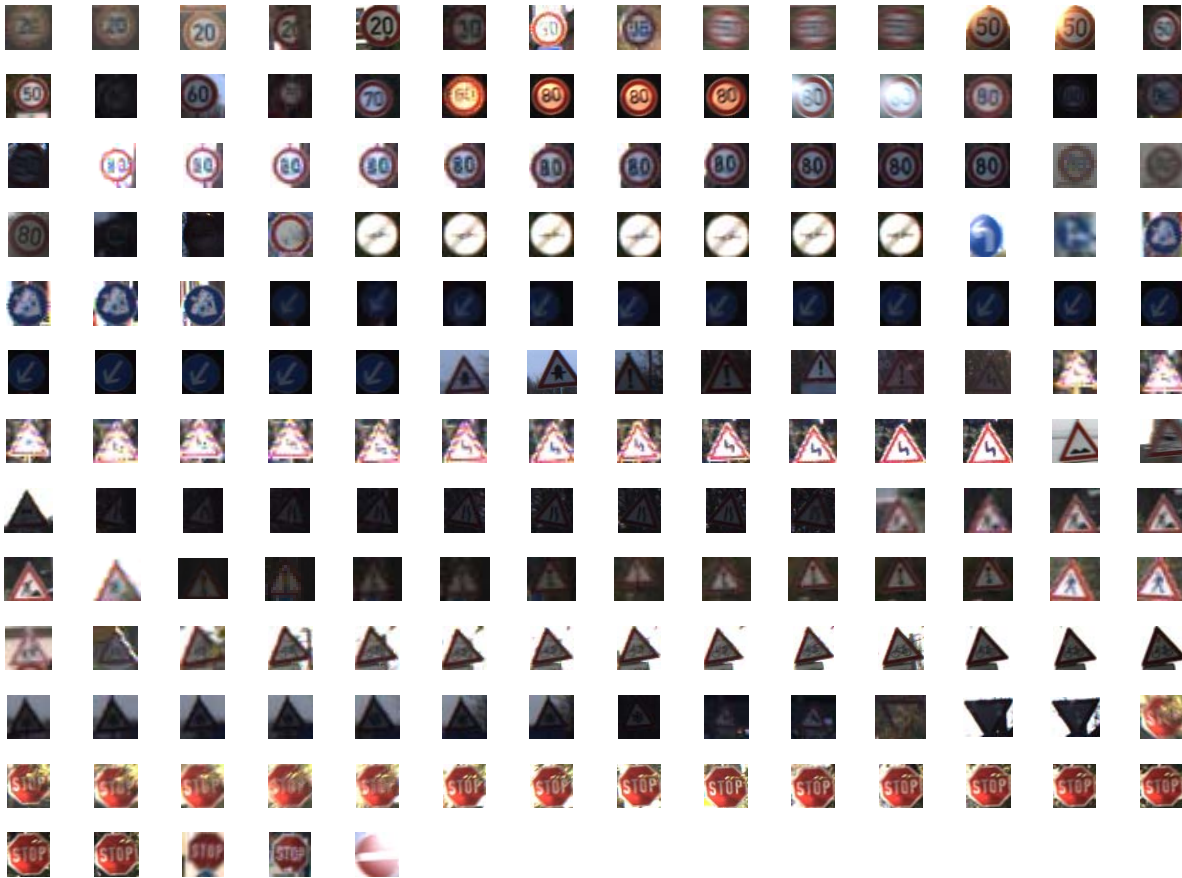


Fig. 9. All misclassified traffic sign images