Machine Learning based Number Plate Detection and Recognition

Zuhaib Ahmed Shaikh, Umair Ali Khan, Muhammad Awais Rajput and Abdul Wahid Memon

Department of Computer Systems Engineering, Quaid-e-Awam University of Engineering, Science & Technology Nawabshah, Pakistan

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Abstract: Automatic Number Plate Detection and Recognition (ANPDR) has become of significant interest with the substantial increase in the number of vehicles all over the world. ANPDR is particularly important for automatic toll collection, traffic law enforcement, parking lot access control, and gate entry control, etc. Due to the known efficacy of image processing in this context, a number of ANPDR solutions have been proposed. However, these solutions are either limited in operations or work only under specific conditions and environments. In this paper, we propose a robust and computationally-efficient ANPDR system which uses Deformable Part Models (DPM) for extracting number plate features from training images, Structural Support Vector Machine (SSVM) for training a number plate detector with the extracted DPM features, several image enhancement operations on the extracted number plate, and Optical Character Recognition (OCR) for extracting the numbers from the plate. The results presented in this paper, obtained by long-term experiments performed under different conditions, demonstrate the efficiency of our system. They also show that our proposed system outperforms other ANPDR techniques not only in accuracy, but also in execution time.

1 INTRODUCTION

The significant increase in number of vehicles has invoked the need of automatic surveillance system. Specifically, for automatic number plate detection and recognition system, image processing based solution is more accurate due to the following reasons: (i) images contain a lot of information which can be utilized from different perspectives, (ii) the availability of high-resolution, high dynamic range and speedy cameras has made it possible to capture a scene and analyze it under different lighting conditions, (iii) image processing based solutions for traffic surveillance are cost-effective, small-sized, portable and robust.

An image processing based ANPDR system is likely to avoid the need of larger, expensive and heavy sensors such that the required information can be extracted from a single image. However, such a system also faces some dedicated challenges such as: (i) computational efficiency, (ii) robustness with multi-scaled and skewed images, (iii) robustness with distorted images, and (iv) acceptable accuracy under different lighting conditions.

Integrating image processing with machine learning techniques results in an adaptive and more accurate system. Instead of finding specific features in images in order to locate the number plate, training a number plate detector with pre-extracted features results in a robust and computationally-efficient system. Such system can be efficiently implemented on an embedded platform to achieve mobility and compatibility for several tasks.

In this paper, We propose a robust and computationally-efficient ANPDR system. In offline processing (performed once), we train a number plate detector using Deformable Part Models (DPM) (Felzenszwalb et al., 2010)(Felzenszwalb et al., 2008) and SSVM which can then be applied online for extracting number plates from the captured images. The extracted plates are further enhanced using several image processing operations and then input to an OCR module for recognition. Our proposed method requires a small number of training samples (25-30 images) without requiring any negative samples. Additionally, the proposed technique can be used to train any classifier for detecting and extracting any object of interest in the images.

The rest of the paper is organized as follows. In section 2, we discuss the existing ANPDR techniques along with their pros and cons. Section 3 gives a theoretical background of deformable part models. Section 4 provides a brief overview of SVM and SSVM. Section 5 describes the overall methodology along with several image enhancement operations. Section

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6 provides some experimental results and comparison with the existing techniques. Section 7 concludes the paper.

2 RELATED WORK

Relevant literature demonstrates a number of ANPDR techniques. In (Hongliang and Changping, 2004), authors propose a number plate extraction method that is based on edge detection and analysis as well as morphological operations. In (Le and Li, 2006), authors propose another hybrid method that detects edge lines in the edge map and computes a weight based edge density map. Regions with the densest edges are selected as candidates and further refined. Another edge-based method (Qiu et al., 2009) finds the region of interest through various steps and then analyzes the region of interest by the inner and outer shape features of number plate. A common drawback of all these edge-based methods is that they result in high false rate in presence of rich features and similar shape in images. The technique proposed in (Zhou et al., 2012) extracts Scale-invariant Feature Transform (SIFT) features of each character in the number plate and generates a respective principle visual word unsupervised clustering. The geometrical information contained in each visual world is used to filter false feature matches. However, this method does not deliver an acceptable accuracy for low-resolution and distorted images which is an inherent limitation of SIFT features.

Another technique proposed in (Baggio, 2012) applies a number of operations on image such as Sobel filter, threshold operation, close morphologic operation, mask on one filled area, detection of potential plates, and linear SVM training. After detection, the number pate is fed to an OCR based on a three-layer neural network to extract the characters of detected number plate. This method is not robust for different scaling images, especially those with tilted plates. In (Prates et al., 2013), the authors use Histogram of Orientated Gradients (HOG) for number plate detection. This approach builds a pyramid of images that is scanned using a sliding window approach. HOG features are extracted for the regions of interest and provided to a linear SVM classifier. This approach can flexibly work with images with different scaling. However, the linear SVM is prone to discarding prior data distribution information within classes due to major focus on margin maximization.

3 DEFORMABLE PART MODELS

In contrast to HOG features (Dalal and Triggs, 2005) discussed in the previous section, Deformable Part Models (DPM) are more effective because they use spatial-part filters for sub-objects which result in significant improvement in detection accuracy.

DPM models are basically derived from HOG features. HOG method is based on evaluating well-normalized local histograms of image gradient orientations in a dense grid. In order to extract the HOG features, the image window is divided into small spatial regions (cells) and a local 1-D histogram of gradient directions or edge orientations is computed for each cell. The combined histogram entries form the representation. For better performance, a measure of local histogram energy is accumulated over larger spatial regions (blocks). The results are then used to normalize all cells in the block (Dalal and Triggs, 2005).

DPM models use a star-structured part-based model defined by a root filter plus a set of part filters and deformation models (Felzenszwalb et al., 2010). Each part model specifies a spatial model and a part filter. The spatial model defines a set of allowed placements for a part relative to a detection window and a deformation cost for each placement. The score of a detection window is the score of the root filter on the window plus the sum over parts, the maximum over placements of that part, and the part filter score on the resulting sub-window minus the deformation cost. Both root and part filters are scored by computing the dot product between a set of weights and HOG features within a window (Felzenszwalb et al., 2008). Figure 1 shows the construction of a feature pyramid for a number plate. The pyramid is obtained by extracting HOG features of each level of a standard image pyramid. The root filter is placed near the bottom of the pyramid and the the part filters are placed near the top of the pyramid. The features extracted this way from all the training samples are then input to a SSVM training algorithm to construct a number plate detector.

4 TRAINING NUMBER PLATE DETECTOR

For training a number plate detector from the extracted features, we need margin based parameter learning that has recently become popular in image processing. It can be performed with Support Vector Machine (SVM) which is one of the most popular machine learning techniques used for classifica-

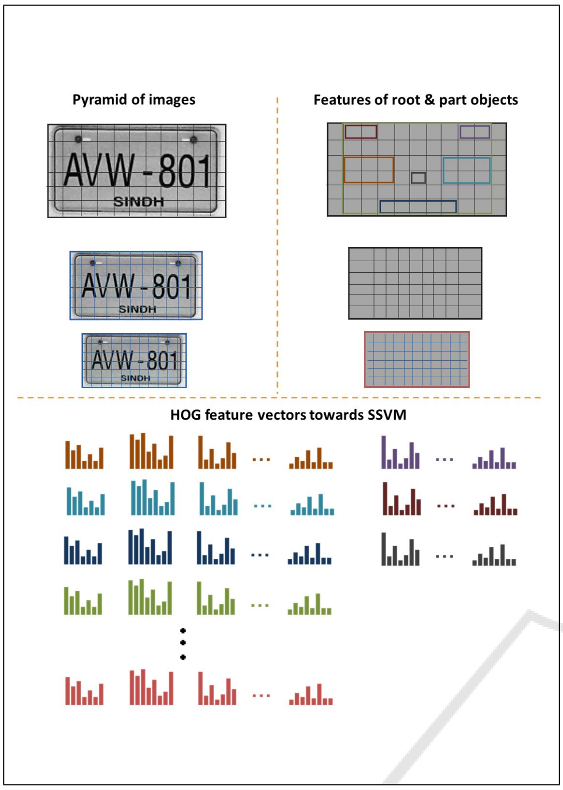


Figure 1: Feature pyramid for a number plate.

tion and regression analysis. SVM discovers the optimal boundary between two classes in the vector space on probabilistic distribution of training by finding hyperplanes. The extracted features of number plates $x \in X$ are used for training with classes $Y \in \{-1, +1\}$, where $+1$ and -1 represents presence and absence of number plate, respectively. The hyperplanes are found with $w^T x + b$, where w^T is optimal or minimum weight from vector of weights for each feature that resembles with a class $y \in Y$ and b is a constant called bias constant (Cortes and Vapnik, 1995).

The traditional linear SVM is a binary classifier which can make only simple predictions (e.g., yes or no). In contrast, Structured SVM (SSVM) (Nowozin and Lampert, 2011)(Wendel et al., 2011) is a more generalized form of SVM which not only inherits the appealing features of linear SVM (e.g., convex training, learning non-linear rules, etc), but also results in much higher prediction accuracy than linear SVM (Joachims et al., 2009b). Although SSVM is specially designed for parsing and more complex predictions in the form of labeled trees (e.g, natural language processing), its higher prediction accuracy and the capability of learning complex outputs (Joachims et al., 2009a) are the appealing features to use it for training a number plate detector.

In SSVM, a weight vector w_y is associated to each class y. During the training, a score is computed for a given feature and its class label by the following rule,

$$f(x,y) = w_y \phi(x) \tag{1}$$

where $\phi(x)$ represents the vector of the extracted features from x. SSVM uses the following prediction rule to map x to the class having highest score.

$$h(x) = \arg\max_{y \in Y} f(x,y) \tag{2}$$

The value of y giving the maximum score defines the predicted class. SSVM search in the parameter space of $f(x,y)$ is directed to find the weights $w = (w_1, \dots, w_k)$ that satisfy the following inequality.

$$f(x_i, y_i) > \max f(x_i, y_{incorrect}) \tag{3}$$

This leads to the formulation of a parameter vector for which $f(x,y)$ always produces the highest score to the correct output. SSVM optimization problem can now be expressed as follows,

$$\min h(w) = \frac{1}{2}||w||^2 + \frac{D}{N} R(w) \tag{4}$$

where

$$R(w) = \sum_{i=1}^{N} \max_{Y}(c(i,Y) + f(x_i, Y|w) - f(x_i, y_i|w)) \tag{5}$$

In equation 5, x_i represents the i^{th} training sample, y_i denotes the correct label for the i^{th} training sample, and $c(i,Y)$ is the cost of predicting that the i^{th} training sample has a label of Y. For the correct label of i^{th} sample, cost becomes zero. $R(w)$ defines the degree of error in predicting the label of the i^{th} sample using parameters w. It is zero when the correct label is predicted and becomes large for wrong outputs. That is, the objective function (equation 4) is minimizing a balance between making the weights small and fitting the training data. The degree of fitting the data is controlled by $D > 0$.

5 OVERALL ANPDR SYSTEM

The overall ANPDR system proposed in this paper is shown in Figure 2.

The various component of the overall system are as follows.

5.1 Offline Processing

The offline processing involves collecting the image dataset for training, extracting the DPM features from

Figure 2: The proposed ANPDR System.

the Regions of Interest (ROI), and training a number plate detector using SSVM. We obtain images of vehicles having number plates from different locations. For the training purpose, we use only 25-30 images with VGA resolution. For extracting DPM features, the ROIs are marked manually by drawing rectangles around the number plates and extracting their coordinates which represent the positive training samples. The negative samples include the entire image other than the ROI. Figure 3 shows some images from our dataset.

Figure 3: Example images from our dataset.

After preparing the image dataset, we extract the DPM features from the ROIs as described in section 3. The extracted feature vectors are then input to the SSVM for training the number plate detector. Figure 4 shows the construction of the number plate detector.

5.2 Online Processing

In online processing, the trained number plate detector is applied to the images captured from a camera. The detector searches for the number plates in the successive images and, if found, returns the plate's coordinates. Figure 5 shows the number plate detection with the detector trained with SSVM.

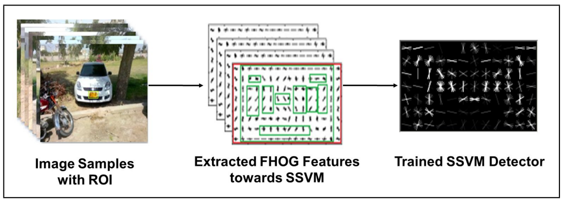


Figure 4: Construction of the number plate detector.

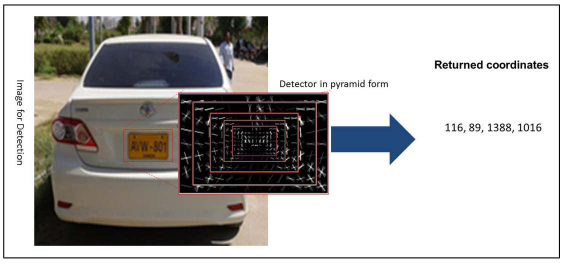


Figure 5: Number plate detection with SSVM detector.

After locating the number plate, it is cropped from the image and the following enhancement techniques are applied on the extracted image.

5.2.1 Bilateral Gaussian Filtering

A bilateral Gaussian filter is applied on the cropped image to remove noise from the image. The filtering radius is set to 5. Whereas, the sigma-color and sigma-space is set to 80 from different experimental results.

5.2.2 Adaptive Thresholding

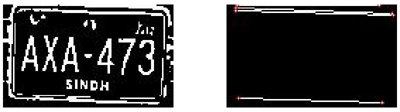
The filtered image is converted into gray scale and an adaptive threshold is applied to binarize the image for handling different lighting conditions. A new intensity value for each pixel is computed by taking the weighted sum of the neighboring pixels in radius r. The weights are a Gaussian window which performs better for textual images.

5.2.3 De-skewing

The extracted number plate may have some skewness which affects the recognition accuracy of the OCR. Therefore, the skew angle of the binary image is calculated using probabilistic Hough transform. We form some dense horizontal lines along the adjacent pixels and calculate their mean angle d_θ using equation 6,

$$d_\theta = \frac{\sum_{i=1}^{n} \arctan^{-1}\left(\frac{y_{2i}-y_{1i}}{x_{2i}-x_{1i}}\right)}{n} \tag{6}$$

where x_{ji} and y_{ji} represent the end points of the n lines. We then create a rotation matrix according to the computed skewness and multiply it with the center of the binary image if $d_\theta < -2.50$ or $d_\theta > +2.50$. Figure 6 shows the formation of dense horizontal lines to compute skewness.

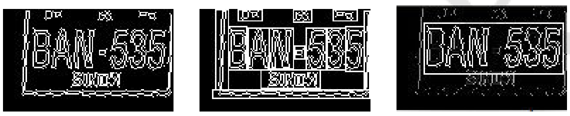


(a) Extracted plate (b) Finding skewness

Figure 6: Computing skewness from dense horizontal lines.

5.2.4 Extracting the Numbers Region

The de-skewed image still contains unnecessary parts which create muddle during OCR. For removing these parts and extracting the characters region, contour operation is applied and a bounding box around each character in the plate is computed. We find the region of interest containing only characters from the coordinates of the bounding boxes of first and last character. All other bounding boxes having area less than a certain threshold are discarded. The region of interest is cropped and inverted using a binary threshold to increase accuracy of the OCR operation. Subsequently, we use an open-source engine Tesseract (Tesseract-OCR,) for optical character recognition and extracting the numbers from the image. Figure 7 shows the selection of ROI from the bounding boxes.



(a) Extracted plate (b) Bounding boxes (c) Region of interest

Figure 7: Extracting the ROI from bounding boxes.

6 EXPERIMENTAL RESULTS AND EVALUATION

We train the number plate detector with only 25-30 images, each annotated with rectangles that bound each number plate in the image. We then create an image pyramid of 6 levels for each image and the DPM model is applied over each pyramid level in a sliding window fashion. We use a sliding window of size 100×60 pixels, however, it can be changed according to the number plate dimensions for a particular region. The extracted feature vector is then sent to SSVM for training. We control the degree of fitting the data by setting $D = 6$. In general, a bigger D encourages to fit the training data better, however, a too large value might lead to over-fitting. The training continues until $R(w)$ in equation 4 is less than a certain threshold ε. In order to solve the SSVM optimization problem more accurately, we set ε to a smaller value, i.e., $\varepsilon = 0.001$. The trained detector is then tested for a number of different scenarios. Figure 8 shows all the stages of number plate detection and recognition. Note that our number plate detector can efficiently detect multi-scaled and skewed number plates. In Figure 8b, the detector is able to detect the distant number plate which is seen through the windscreen of a car. We calculate the False Positive Rate (FPR) and the overall accuracy of our detector by the following equations.

$$FPR = \frac{no.\ false\_positive + no.\ false\_negative}{no.\ test\_cases} \times 100 \quad (7a)$$

$$Accuracy = 100 - FPR \quad (7b)$$

The detection accuracy, false positive rate, recognition accuracy, and the overall execution time of our detector are given in Table 1. The experiments were performed on a PC with 2.5 GHz CPU and 6 GB RAM.

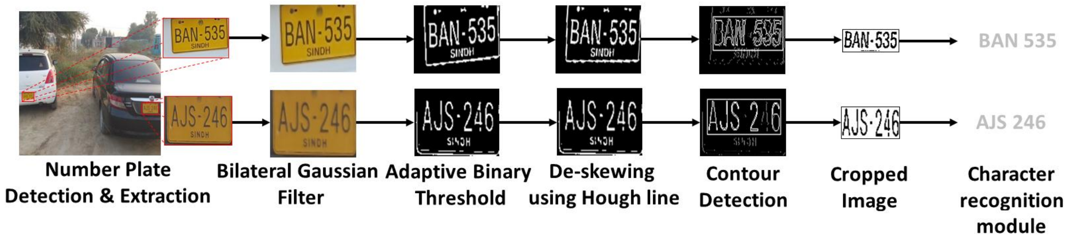
We also compare the performance of our ANPDR system with some existing ANPDR techniques such as (i) a hybrid method (Le and Li, 2006) comprising line detection in the edge map, obtaining an weight based edge density map, and refining the densest edges, (ii) a vertical edge detection based method (Qiu et al., 2009), (iii) a method based on the edge statistics and morphology (Zhou et al., 2012), and (iv) a method using the visual bag-of-words model (Zhou et al., 2012). For the sake of fair comparison, we use a common image dataset (Caltech Cars Dataset,) with the same machine configuration. Table 2 shows our comparison results.

Table 1: Evaluation of the proposed ANPDR system.

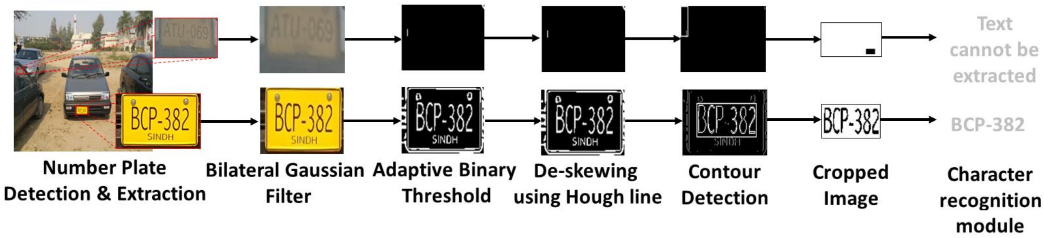
Evaluation parameter	value
Detection accuracy	96.03%
Recognition accuracy	78.00%
False positive rate	03.97%
Detection+Extraction time	02.80 sec

Table 2: Comparison of the proposed ANPDR with existing ANPDR techniques.

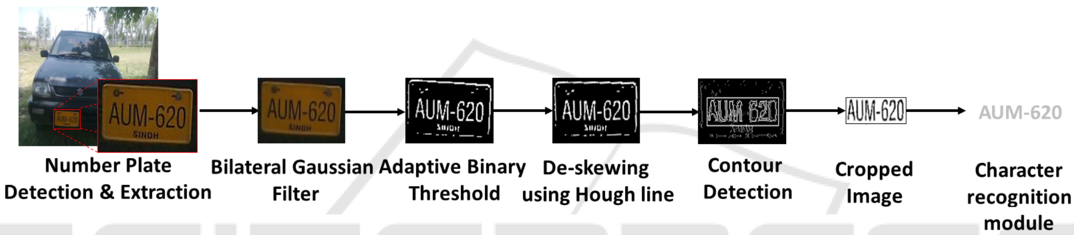
Technique	Accuracy	FPR	Time
Hybrid	71.40%	28.64%	38.86 s
Vertical edge	70.50%	29.50%	01.40 s
Edge statistics	74.10%	25.94%	07.09 s
Visual words	95.50%	04.50%	07.17 s
Proposed ANPDR	96.03%	03.97%	02.80 s



(a) Multi-scaled, skewed plates detection



(b) A difficult case of detecting occluded and distant number plate



(c) Detecting a skewed number plate under shade

Figure 8: Testing the detector for different cases.

From Table 2, it is evident that our proposed ANPDR system not only outperforms other techniques with respect to accuracy, but also execution time.

7 CONCLUSION

In this paper, we have proposed an automatic number plate detection and recognition technique using deformable part models for extracting the number plate features and structural support vector machine for training a number plate detector. The number plate extracted from the scenes captured by a camera are further enhanced for improving the accuracy of optical character recognition. The trained detector can efficiently detect multi-scaled and skewed number plates under varying light conditions. The results presented in this paper show that our proposed ANPDR technique delivers a higher accuracy with much less execution time as compared to other ANPDR techniques. Additionally, the proposed technique can be easily implemented for ANPDR in any region with small changes in the training parameters.
In future, we aim to migrate our ANPDR system on an embedded platform with Compute Unified Device Architecture (CUDA) capability for increased portability and faster processing by parallel computing. Additionally, we aim to further improve the accuracy and detection time by defining a region of interest specific to the scene. Our future research is also focused on improving and optimizing the image enhancement part of the ANPDR for delivering higher accuracy under extremely low light conditions.

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