License Plate Detection using NMF with Sparseness constraints through still Images

Muhammad Jawad[1], M. Yasin[1], M. Saquib Sarfraz[1, 2]

[1]Computer Vision Research Group (COMVis), COMSATS Institute of IT, Lahore Pakistan

[2]Institute for Anthropomatics, Karlsruhe Institute of Technology, Karlsruhe, Germany

{mjawad, yasin.muhammad,ssarfraz}@ciitlahore.edu.pk

ABSTRACT

Real time license plate detection and recognition from CCTV videos is an active research problem. Most of the existing solutions are reasonably successful and efficiently fast but most of them are effective only in controlled environments where light intensity, illumination, orientation of plate do not vary much and image resolution is not too low. Two crucial image processing steps in an LPDR system are: (a) localization of license plates within an image and (b) recognition of license plate using an OCR system. The aim of this paper is to address the localization problem for low quality images. We use a novel, and robust framework to build a license plate detection system. Implemented system is intelligent enough to tackle varying environment conditions automatically with low hardware requirements and less complex algorithm. Experimental results on database collected under varying conditions demonstrate the robustness of the proposed approach.

Keywords

Automatic License plate Detection and Recognition (ALPDR), non-negative matrix factorization (NMF), Histogram of oriented gradient (HOG), Local Energy based Shaped Histogram (LESH)

1. INTRODUCTION

Automatic License plate detection and recognition (ALPDR) is one of the vital areas of research in computer vision and image processing over the past two decades. The demand of ALPDR System is increasing exponentially with the alarming increase in crime rates throughout the world. The objective of an ALPDR system is detection of license-plate-like regions in either still images or CCTV videos obtained through a road-side CCTV camera. The task becomes quite challenging when there is a wide variation in license plate shape, size and color. ALPDR can be put to use in various application areas including automatic highway toll collection, automatic parking control, traffic laws enforcement, border security, and crime prevention.

A number of techniques have been developed in the recent past for efficient detection of the license plates-like regions based on both still images and/or videos. A rank filter based approach is used by Martinsky [13] for the localization of license plate but the technique fails for skewed license plates. Most of the proposed works for ALPR systems [1, 6, 7,8,9] apply edge based feature extraction techniques for the localization of license plates. However, most of techniques are applicable only under highly controlled environment and fail of offer reasonable detection accuracy for non-uniformly illuminated license plates. A license plate localization and recognition technique is developed using attributes of the plates and neural network [14], this technique gives good results for localization but poor results on recognition. Mean shift algorithm [16] is another technique used for localization of license plate; rectangularity attribute, edge density, and aspect ratio are used as feature in Mahalanobis distance based classifier for detecting the correct license plate among several candidates. This method is robust as long as the color of the license plate differs from the color of the body of the vehicle. In another approach [15] Hough transform for line detection is proposed on the assumption that the shape of license plate is determined by lines, but the approach also fails to give good results on skewed license plates. Mathematical morphology based method is another approach proposed by [18]. Parallelogram and Histogram based Vehicle License Plate Detection model is proposed by [10]. Apart from all these techniques many researchers prefer a hybrid detection algorithm, where license plate location method based on characteristics of license plate shape, character connection and projection [19]. Not much work has been done on the localization of license plates for the regions (countries) where there is no standard for the size and aspect ratio of License plate like in south Asia.

In this paper a robust framework named non-negative matrix factorization (NMF) [4] is proposed for the localization of license plates. This discriminative framework is based on part-based approach which is useful in reconstruction of novel areas (license plate like regions). NMF has been successfully used in the past in applications like; pose primitive based human action recognition [3], Eye detection [2], and Aging Estimation [17]. NMF is used for the first time in license plate detection in our work. It is equally applicable for extracting candidate (license-plate-like) regions in both images and videos with relatively good degree of accuracy. The framework can also be used in conjunction with a number of feature extraction algorithms. There is no standard database available online for testing and comparison of a newly developed algorithm with the other existing methods. We created our own database of car images for the current experiment. The license plates vary significantly in size, shape and relative location on vehicle. License plate detection results are compared with some known classifiers like nearest neighbor and Ada-boosting and results are comparably better.

In subsequent sections key modules of the present work are described.

2. FEATURE EXTRACTION

Three different types of features extraction techniques are tested for robust visual object (License Plate) recognition on connected components found in an image. These feature extraction algorithms are very functional to locate interest points like corners, edges, and valleys in an image. Then feature vector of each detected candidate region is classified with the help of training data.

First feature descriptor used for this purpose is the Local Energy based Shaped Histogram (LESH) [11], which is based on local energy model of feature perception (Koveri 2000) described as:

$$E = \frac{\sum W(x)\lfloor A_n(x)(\cos(\varphi_n(x)-\bar{\varphi}(x)) - |\sin(\varphi_n(x)-\bar{\varphi}(x))|) - T\rfloor}{\sum_n A_n(x)+\varepsilon} \quad (1)$$

Gabor filtering is used to obtain the local energy of an image which gives stable response in terms of high energy on edge corners. This algorithm generates 8 bins local histogram 'h' as:

$$h_{a,b} = \sum w_a \times E \times \delta(L-b) \quad (2)$$

Where 'b' represents current bin, 'L' is the orientation label map, 'E' is the local energy extracted from equation 1, and 'w' represents Gaussian weighting function at required region 'a' (see equation 3).

Figure 1. Examples demonstrating the connected components found in the images, where Red rectangular bounding box represents true localization of license plates.

Figure 2. Examples demonstrating the false localization of candidates regions in the test images.

$$w_r = \frac{1}{\sqrt{2\lambda\sigma}} e^{[(X-a_{x0})^2+(y-a_{y0})^2]/\sigma^2} \quad (3)$$

In order to keep the spatial information of the image, we extracted 8 bin histograms by taking into consideration local energy along 8 filter orientations on 16 image partition then these local histograms are concatenate together, which makes 128-dimentional feature vector containing all spatial information of a connected component found during candidate selection.

Second descriptor used as an alternate of LESH is Histogram of oriented gradient (HOG) presented by [12], it is a well-known descriptor which use distribution vector of edge direction (gradient). It is useful for applications like License plate detection where edge orientation information helps for detecting an object shape and form in a well defined manner. In order to extract this feature descriptor, we divide the image (connected component) window into 4×4 spatial regions, then computing 9-bin histogram of edge orientations (directions) for each region. In the end these 16 histograms are concatenate together to form a 144-Dimensional feature vector which contains edge direction information for entire image window.

Third feature descriptor used is Scale Invariant feature Transform (SIFT) by [5]. These features are invariant to image scale and rotation and partially invariant to illumination change and 3D camera view point. This feature extraction approach is well localized in both frequency and spatial domain and highly distinctive. In this algorithm we have used 4×4 array of histograms with 8 orientation bins in each. Therefore 128-Dimension feature vector is extracted for each image window.

3. PROPOSED FRAMEWORK

In the present work we have developed a new technique for the localization of license plates in captured images from surveillance cameras. This Proposed framework can be observed clearly from Figure 3. In the subsequent sections the key modules involve in the present framework has been discussed.

3.1. Candidate Regions selection

Standard connected component analysis algorithm is applied on the pre-processed images for the selection of suitable candidate (license plate like) region (s). This algorithm scans whole image by moving along the rows from left to right and group all the pixels into component having same property (binary values) see Figure 1. This framework is equally applicable on both gray scale and binary images. Geometrical constraints are applied in order to minimize the number of selected components found in an image. These constraints are based on prior knowledge of license plates sizes used locally and globally like width-to-height ratio of license plates, so applied constraint will only select candidates having ratio b/w 1 to 4. Width and Height lengths of license plates are 150×300 pixels and 40×100 pixels depending upon the resolution of the images taken. Prior knowledge tells that eccentricity of license plates like regions should be less than 0.8. These connected components are then used for training and testing in NMF based proposed detection framework.

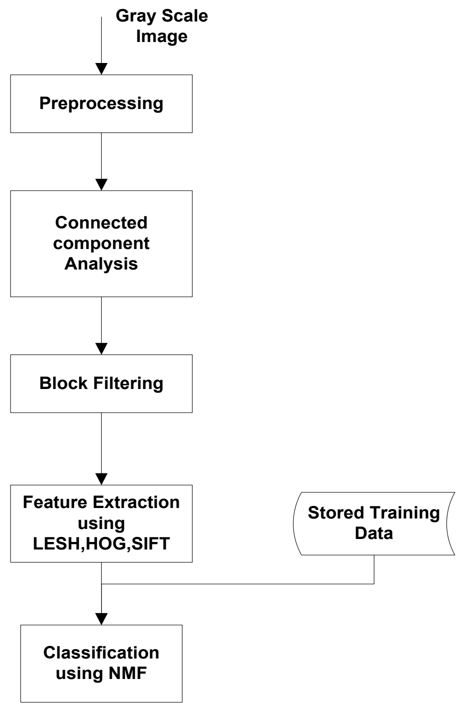

Figure 3. Block Diagram of the Proposed Framework

3.2. Classification using NMF

Non-Negative Matrix Factorization (NMF) [4] is used for classification of License plate like regions in test images. Main problem in most data-analysis problems is to find an appropriate representation of data. A functional representation usually makes latent structure in the data explicitly and often reduces the dimensionality of data. Non-negative matrix factorization is a suitable method for finding such a representation. Non-negativity constraints make NMF additive (allowing no subtraction) in contrast to other linear representations like PCA and ICA and this algorithm can only be applied on a non-negative data set [feature vector '*F*']. In our experiment three different types of feature descriptors are tested and all of them are non-negative. NMF is the part based approach which makes it quantitatively better. Another useful property of NMF is the sparse representation of data; benefit of such representation is that it encodes much of data using few 'Active' components which makes encoding easy to interpret. e.g. when we are trying to learn useful features from a dataset of images, it might make sense that matrices should be sparse. In NMF a linear data representation is simply a factorization of descriptor vector 'F' written as $F = BW$, where 'B' is known as the basis vector and 'W' be a weight matrix and both are constrained to be non-negative, this factorization process is so powerful that we can approximately reconstruct descriptor vector 'F' again by multiplying 'B' and 'W' this reconstruction power of NMF can be observed from Figure 5. NMF use standard multiplicative rule [4] for approximate factorization $F \approx BW$.

In the training phase positive (B_pos, W_pos) and negative (B_neg, W_neg) parameters vectors were extracted independent to each other, where parameter B_pos is the basis vector contains information of meaning-full parts of positive Samples (license plate). Initial data analysis stated that 80-100 positive and negative training samples each are sufficient for getting desired detection results. During testing W_test is computed from feature vector (F_test) of each connected component found in a test image by holding *'B'* fixed (extracted during training phase) using inverse NMF technique based on standard iterative algorithm as described in equation 4.

$$B = [B\_pos \quad B\_neg] \tag{4}$$

Key aspect of this algorithm is the use of additive combinations of weights that's why new coefficient vector W_test composes of separate coefficients of positive and negative weights like $W\_test = [W_{pos}^{test} \quad W_{neg}^{test}]$, so positive and negative appearances can be decoupled. License plate detection from 'n' number of connected components found in each image is based upon likelihood ratio, calculated by [3] as given in equation 5.

$$L = \frac{P(\mathrm{Im}/neg)}{P(\mathrm{Im}/pos)} \approx \frac{1 - \left|(F_{new} - F_{pos}^{new} / \left|F_{new}\right|)\right|}{1 - \left|(F_{new} - F_{neg}^{new} / \left|F_{new}\right|)\right|} \tag{5}$$

Here, $F_{pos}^{new} = B\_pos * W_{pos}^{test}$, $F_{neg}^{new} = B\_neg * W_{neg}^{test}$, and $F_{new} = F_{pos}^{new} + F_{neg}^{new}$ respectively.

From the repetition of experiment it is concluded that connected component which has likelihood ratio close to '1' should have more probability to be a license plate, so adjusted threshold of likelihood ratio for this experiment is [0.9-1.1].

Figure4. Examples demonstrating training Samples,

First Row: Positive Sample images (License plates),

Second Row: Negative Sample Images (Non-license plates)

Figure 5. Examples demonstrating the power of reconstruction of NMF

First Row: Original License plates

Second Row: Reconstructed License plates

4. EXPERIMENT AND RESULTS

In order to show the efficiency of the algorithm dataset for the current experiment is collected from a major town in local area. Different surveillance cameras were installed at different locations like car parking, road crossing at different height places from the road surface. The complete image dataset comprises of more than 2000 frontal and a rear view of different types of vehicles under varies conditions of lighting, color, shadows, pollution levels and camera angles. Images were captured at a frame rate of 25fps and resolutions of the images are mostly low. We have used half of the captured images for training and half are used for testing in the current experiment which includes complete license plate like regions. Data set used for this experiment is also available online at (http://comvis.ciitlahore.edu.pk/).

4.1. Training dataset generation for NMF Framework

From a large number of images, we have in the dataset, rectangular license plate regions are extracted manually and stored separately. This way, a dataset of positive samples is created and all the images are marked as positive (+1). In the same way, random sub-images of the size of license plate images are cropped from non-plate regions from the dataset and are labeled as negative (-1). The feature vector (LESH, HOG or SIFT) is computed for every image in both the classes and concatenated to form feature matrix ‘F’. This Matrix is factorized into basis matrix ‘B’ and weight matrix ‘W’ using NMF. These training matrices are used for real time localization of license plates in testing phase.

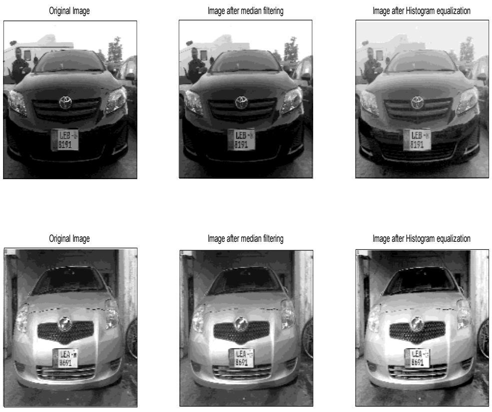

Figure 6. Representing the first phase of the algorithm, where standard pre-processing techniques are applied to increase image quality. First Column contains Original input images, Second Column contains images after removing salt & pepper noise, Third Column is representing image after contrast enhancement.

4.2. License Plates Localization

Test images are taken under varying environment conditions through multiple cameras over different day timings, so they include embedded salt and pepper noise and huge contrast variations.

Firstly, standard pre-processing techniques are applied sequentially to alleviate or attenuate some of the artifacts mentioned earlier. Median filtering is applied on gray images to reduce “Salt and pepper” noise, it replaces gray value of a pixel by the median of the gray values of its neighbors for this purpose we have used default 3×3 neighborhood of a pixel. Contrast of images is enhanced by using histogram equalization technique. Results of pre-processing are shown in Figure 6. Although the exact location of license plate is unknown in this phase, this process locally balances the illumination in different parts of an image.

Training set for the experiment which comprises of positive (license plates) and negative (non-license plates) image samples (100 each) see Figure 4. We have compared the performance of the proposed NMF based classifier against K-nearest neighbor (KNN) where K = 3, and Ada-boost (decision Stump as weak classifer) on the basis of Precision/Recall/F-Score and Accuracies on both the training and test datasets (See Table 1). Although the processing time of NMF is more than the other two classifiers but there is significant improvement in terms of Precision, Accuracy and F1-Score.

NO	Descriptor		Precision rates/ classifier		
			NMF	**KNN**	**ADA-boosting**
1	**LESH**	Precision	72%	57.1%	48.95%
2		Recall	87%	92.1%	49.47%
3		Accuracy	70.2%	61.5%	48.94%
4		F1-Score	0.809	0.705	0.4920
5		Processing Time/ image	0.8 sec	0.7 sec	0.55 sec
1	**HOG**	Precision	68.3%	52.5%	54.8%
2		Recall	76.3%	80.8%	56.3%
3		Accuracy	70.5%	57.3%	57.6%
4		F1-Score	0.721	0.681	0.555
5		Processing Time/ image	0.7 sec	0.6 sec	0.42 sec
1	**SIFT**	Precision	65.2%	50.2%	52.6%
2		Recall	80.4%	82.4%	62.5%
3		Accuracy	60.5%	56.8%	58.3%
4		F1-Score	0.718	0.618	0.702
5		Processing Time/ image	0.6 sec	0.5 sec	0.3 sec

Table 1. Comparison of Precision rates of three different Classifiers for testing data

5. CONCLUSION AND DISCUSSION

NMF based car license plate detection algorithm is proposed and discussed in this paper. NMF is robust framework which is used for the first time as a classifier in license plate detection application precisely with high degree of accuracy. Our experimental results show that NMF can be a useful classifier used in ALPDR systems. Robustness of this method is verified by comparison with other known classifiers on a big mixed dataset taken by us under various conditions because there is no standard dataset available online for testing of such algorithms. Another advantage of this algorithm is the high precisions of detection boxes, so character recognition algorithm can be applied easily which is the next step of our work. There are some vital appealing aspects for future research like candidate selection procedure can be improved to increase detection rates also the processing time of present research work can be reduced by implementation in C++ and open CV for real applications.

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