Skew and Slant Corrections for IR Images in Indian License Plate Recognition Using HCD & HPR

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Abstract: **Character segmentation and detection play a very important role in the license plate recognition (LPR) system. For accurate character segmentation first need is to remove skew from the received license plate for the night vision images. Skew is the angle by which the image seems to be deviated from its perceived steady state position. To solve the problem, a combined approach for skew correction of vehicle license plates (VLP) is proposed which is based on Harris corner detector and Hybrid Proximal Recognition (HPR). First, corner points are extracted as features using Harris corner detector. PCA is applied onto these features to find out the principal component in the direction of maximum Eigen value. This principal component reflects the skew angle of the plate and by using Hybrid method. Then skew and slant correction of the plate for Infrared images is accomplished. Main advantage of the Proposed method is, it is very simple in the Skew correction of VLP images and gives accurate results for the night vision images (IR).**

Keywords: Skew and Slant Correction for Infrared Images, HCD, HPR

I. INTRODUCTION

This work is on the research and development in the area of Indian License Plate Recognition; Problems Associated with recognition of license plates of varying structure and size; frames and formulates a workable Solution for implementing Indian license plate recognition systems in various dynamic conditions using Localization and Correlation based recognition algorithms. The Major contributions of the work are that the Indian License Plate Detection and Recognition in various conditions like high/low luminance, Rainy Conditions and some other problems pertaining to the low quality license plate images. This introductory chapter describes the need of Indian license plate skew and slant detection of cognition system, Structure of Indian License plates; License Plate image pre-processing methodologies. This thesis mainly concentrates on the Skew and Slant Corrections for IR images using Harris Corner Detection [12] and Hybrid Proximal Recognition

II PREVIOUS WORK

Character Segmentation and Skew Corrections have been not been properly segmented / skewed; the image is segmented only for particular size. Especially in the case of blurred images or any shadow images in the LP the character/numbers have been not properly displayed / read. In Line extractor have been working only for single line of the image it have not been working for all kind of double line images of the License Plate In the case of Skewed images, Skew corrections have not been done for blurred images

III PROPOSED SYSTEM

The proposed is the combined approach of Harris Corner Detector and Principal component analysis. In the proposed system, first we extract the license plate form the vehicle and then we apply the algorithm of Harris Corner Detector (HCD) [6] and Principal component analysis (PCA) [4]. Applying Harris Corner Detector and Hybrid Proximal Recognition Noisy response due to a binary window function we are going to use a Gaussian Function Apply Gaussian filtering to suppress noise. This will blurs everything which is smaller than filter size in order to enhance the detection of feature points. Here we use default filter size and value of the sigma (σ) that is 0.5. Sigma's represent the parameter of Gaussian filter. Suppress the corner points below the specified threshold value. This will give the required corner points. Use the index values of the corner points; find out its covariance matrix. Find out Eigen values and its corresponding Eigen vectors. Order them by Eigen value highest to lowest. This will give the component in the order of significance. Ignore the components of lesser significance. Eigenvector with highest Eigen value is the required principal component. Use this principal component to find out skew angle Apply Bayes Soft thresholding to the noisy coefficients .Apply Harris corner detection on the de-noised image finally, rotate the entire image using negative of the skew angle. Rotation of the skewed image can be achieved using bilinear interpolation.

IV SKEW AND SLANT CORRECTIONS

Captured images of signboards in natural scenes often suffer from image deformation due to their orientation in 3D space and projection. Before digit recognition, we try to cancel this as much as possible. We assume characters in the input image are on a planar surface in 3D space. We also assume text lines are arranged horizontally on the planar surface. We denote the equation of each text line in 3D as

$$\mathbf{P}^{(i)}(t) = \begin{pmatrix} P_X^{(i)}(t) \\ P_Y^{(i)}(t) \\ P_Z^{(i)}(t) \end{pmatrix} = \mathbf{Q}^{(i)} + \mathbf{a}t$$

$$= \begin{pmatrix} Q_X^{(i)} + a_X\ t \\ Q_Y^{(i)} + a_Y\ t \\ Q_Z^{(i)} + a_Z\ t \end{pmatrix},$$

Where a = (Ax, aY, aZ) T is a unit vector (i.e., _a_ = 1), which represents the direction of text lines in 3D. When we take the coordinate system so that the viewing direction coincides with the Z-axis, the perspective projection from a 3D point X =(X, Y, Z) onto a 2D image point x =(x, y) T is given by T

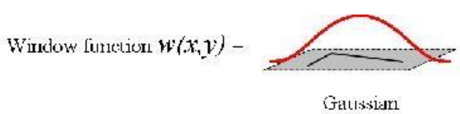
$$x = f\frac{X}{Z}, \quad y = f\frac{Y}{Z}.$$

In our method, the image transformation effect is modelled as skew and slant for the night vision images. First, for the captured image [5], affine transformation for skew normalization is carried out so that the number plates are placed horizontally in the transformed image. After the skew normalization, the remaining deformation effect is modelled as Indian Number Plate slant. It is normalized by another affine transformation. For skew correction, the Harris Corner Detection and Hybrid Proximal Recognition approach is used to determine the skew angle. First, the centres of the regions of the digit candidates are calculated as {(x 1, y 1), (x2, y2), · · · , (x)} [8][12]. Next, all the centres are transformed by ρ = x cos θ +y sin θ. Since the transform is only applied to the centres, the computational cost is quite low. An angle with the maximum number of votes in the ρ - θ parameter space is estimated as the skew angle .Skew correction angle f is given as -a. (We restrict the angle to -45n, y n ◦= f, a = 45.)After the skew normalization, we extract the slant angle by circumscribing digits with tilted rectangles. First, each candidate region is circumscribed with a tilted rectangle

Harris Corner Detection:

Noisy response due to a binary window function

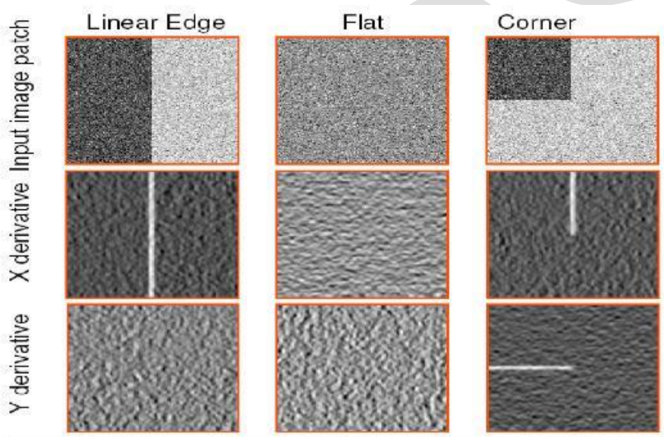
- ➢ Use a Gaussian function

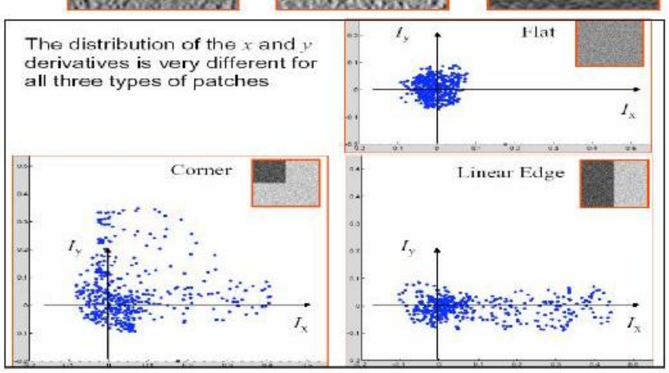


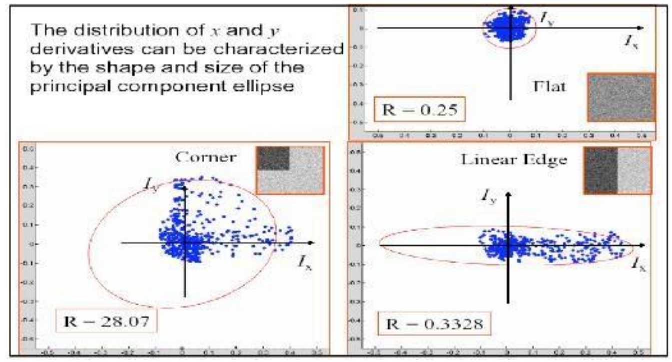
Only a set of shifts at every 45 degree is considered

- ➢ Consider all small shifts by Taylor's expansion

$$E(u,v) = Au^2 + 2Cuv + Bv^2$$
$$A = \sum_{x,y} w(x,y) I_x^2(x,y)$$
$$B = \sum_{x,y} w(x,y) I_y^2(x,y)$$
$$C = \sum_{x,y} w(x,y) I_x(x,y) I_y(x,y)$$







Baye's Shrink

Optimum Bayes estimator for General Gaussian Distributed (GGD) data in wavelet is provided. The GGD distribution describes a wide class of signals including natural images. A wavelet thresholding method for image denoising is proposed. Interestingly, we show that the Bayes estimator for this class of signals is well estimated by a thresholding approach. This result analytically confirms the importance of thresholding for noisy GGD signals. We provide the optimum soft thresholding value that mimics the behaviour of the Bayes estimator and minimizes the resulting error [5]. The value of the threshold in BayesShrink, which is one of the most used and efficient soft thresholding methods, has been provided heuristically in the literature. Our proposed method, denoted by Rigorous BayesShrink (R-BayesShrink), explains the theory of BayesShrink threshold and proves its optimality for a subclass of GDD signals. R-BayesShrink improves and generalizes the existing BayesShrink for the class of GGD signals. While the BayesShrink threshold is independent from the wavelet coefficient distribution and is just a function of noise and noiseless signal variance, our method adapts to the distribution of wavelet coefficients of each scale. It is shown that BayesShrink is a special case of our method when shape parameter in GGD is one or signal follows Laplace distribution. Our simulation results confirm the optimality of R-BayesShrink in GGD denoising with regards to Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) index.

Procedure of Harris Corner Detection

Applying Harris Corner Detector [15][16] and Principle Component Analysis Noisy response due to a binary window function we are going to use a Gaussian Function

- Apply Gaussian filtering to suppress noise. This will blurs everything which is smaller than filter size in order to enhance the detection of feature points. Here we use default filter size and value of the sigma (σ) that is 0.5. Sigma represent the parameter of Gaussian filter
- Suppress the corner points below the specified threshold value. This will give the required corner points.
- Use the index values of the corner points; find out its covariance matrix.
- Find out Eigen values and its corresponding Eigen vectors. Order them by Eigen value highest to lowest. This will give the component in the order of significance. Ignore the components of lesser significance.
- Eigenvector with highest Eigen value is the required principal component.
- Use this principal component to find out skew angle
- Apply Bayes Soft thresholding to the noisy coefficients.
- Apply Harris corner detection on the de-noised image
- Finally, rotate the entire image using negative of the skew angle. Rotation of the skewed image can be achieved using bilinear interpolation.

Only a set of shifts at every 45 degree is considered

- ➢ Consider all small shifts by Taylor's expansion

$$E(u, v) \cong [u \quad v]\, M \begin{bmatrix} u \\ v \end{bmatrix}$$

Equivalently, for small shifts [*u, v*] we have a *bilinear* approximation:

Where M is a 2×2 matrixes computed from image derivatives:

Measure of corner response: (*k* – Empirical constant, *k* = 0.04-0.06)

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Average intensity change in direction [*u*,*v*] can be expressed as a bilinear form:

$$E(u, v) \cong [u \quad v]\, M \begin{bmatrix} u \\ v \end{bmatrix}$$

Describe a point in terms of Eigen values of M: measure of corner response

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

A good (corner) point should have a large intensity change in all directions, i.e. R should be large positive

Hybrid Proximal Recognition

The idea behind the design of hybrid algorithms is very simple. Assume that, for a given computational problem Π, we are given two algorithms, a recursive algorithm A_1 and another algorithm A_2 (usually iterative, although not necessarily so). Let A_1 be asymptotically faster than A_2, with the former exhibiting higher constants in its running time than the latter. We can create a recursive hybrid algorithm H by modifying the code of A_1 in the base case as follows: we introduce a new value of the instance size, say n_0, under which we solve directly using algorithm A_2. The remaining code stays unchanged, apart from substituting recursive calls to A_1 with recursive calls to H.Therefore the code for H will look as follows:

H(i)
if size (i) $\leq n_0$
then return A_2 (i)
DIVIDE step of A_1
RECURSE step of A_1 (but using H for the calls)
CONQUER step of A_1

Our objective in designing H is to obtain the best from both algorithms, namely, keeping the asymptotic behaviour of A_1 but lowering its constants thanks to the use of A_2 on smaller instances. Note that in the code above, the "switching point" n0 between the applications of the two algorithms is a parameter whose actual value must be determined and fixed by the analysis, so to minimize the running time of the hybrid algorithm. In what follows, we will discuss how to proceed analytically to obtain the best choice of n_0

$$E(u,v) = Au^2 + 2Cuv + Bv^2$$
$$A = \sum_{x,y} w(x,y) I_x^2(x,y)$$
$$B = \sum_{x,y} w(x,y) I_y^2(x,y)$$
$$C = \sum_{x,y} w(x,y) I_x(x,y) I_y(x,y)$$

for the case of square matrix multiplication, where we can obtain a hybrid algorithm from Strassen's algorithm and the naive, iterative algorithm based on the definition. The hybrid algorithm H-SMUL for matrix multiplication obtained from Strassen's algorithm SMUL and definition-based algorithm MUL is:

H-SMUL (A, B)
n $\leftarrow$ rows(A)
If n $\leq n_0$
then return MUL (A, B)
DIVIDE step of SMUL
RECURSE step of SMUL (but using H-SMUL for the calls)
CONQUER step of SMUL

Recall that, when n is a power of two, the respective running times T_S (n) and T_M (n) of SMUL and MUL are

$$T_S(n) = 7n^{\log_2 7} - 6n^2$$
$$T_M(n) = 2n^3 - n^2$$

Observe that this recurrence has two parameters n and n_0. Since Strassen's algorithm only works for matrices which are a power of two, it is reasonable to assume that also n_0 be a power of two. Let us now proceed to determine an analytic solution to the above recurrence as a function of its two parameters. From the recursion tree associated with the recurrence, we can collect the following information for values of n > n_0.

V. EXPERIMENTAL RESULTS

To examine the effectiveness of our method, experiments were carried out using 1,500 images containing 10,299 digits. The results of the digit extraction and recognition for the LPR are shown in Table 1. By the candidate extraction method described in Sect. 60,843 digits were extracted from the input images with 10,299 digits (i.e., digit extraction rate of

97.09%), and 9620 digits were correctly recognized from those extracted digits (i.e., correct digit recognition rate of 95.4%). The below Figure shows some examples. When skew and slant normalization was used, the digit extraction rate was almost the same but the digit recognition rate was improved in the LPR, as shown in Table 1[15][17]. If digits have a large deformation effect, some digits were recognized incorrectly without the normalization. The digit extraction method produced 8000 false candidates in the experiments without the skew and slant normalization, as shown in Table 1. On the other hand, after the normalization the number of false candidates was reduced from 8000 to 6,500, as was expected. In the digit recognition, 73.8% of them were rejected properly; however, the rest of them remained. When the method without normalization was applied, the total number of the remaining non digits was 1,500. This improvement is due to the candidate extraction method after skew and slant normalization (Fig. 1). These results show the effectiveness of our skew and slant normalization method. To improve the classifi cation power further, more advanced classifi ers such as SVM [1, 2] can be used instead of the simple template matching technique we used. Our method is based on a couple of assumptions (i.e., digits are assumed to be arranged horizontally on a planar surface and its surface normal is assumed to be close to the viewing direction). Obviously, these assumptions do not always hold.

Fig 1: Results of Digit Recognition

Skew and slant Normalization for IR images	Without Normalization For Infra-Red Images		With Normalization For Infra-Red Images	
Candidate Region	Digit Region	Nondigit Region	Digit Region	NonDigit Region
	97.09%	*1	97.09%	*1
Digit extraction rate	(10,000/10,299)	8000	(10,003 / 10,299)	6,500
Digit recognition	94.2%	80.6% *2	95.4%	73.8 % *2
	(9420 / 10,000)	(6,452 / 8,000)	(9620 / 10,018)	(4,800 / 6,500)

***1**: The value indicates the number of extracted non-images in night vision regions

***2:** This indicates the rejection rate of night vision regions

VI. CONCLUSION

In this paper, we propose a method to recognize digits in a natural scene in night visions, such as Indian License Plate numbers on a Vehicles License Plate. Unlike traditional character recognition problems, since the text surface is in 3D space that too in night visions (Infra-Red Images), we have to deal with the image transformation effect due to orientation in 3D space. Since digits in Infra-Red images often have skew and slant, we have to correct both the skew and the slant before digit recognition. We presented a skew correction method based on the Harris Corner Detection and Hybrid Proximal Recognizer. In our method, since the Harris Corner Detection is applied only to centre points and each edges of the extracted candidate digit regions, fast skew correction is made possible. After skew normalization, the slant is corrected by circumscribing digit patterns with tilted rectangles. The rectangle is tilted 45. The slant angle is calculated using the vertex positions of the rectangle, and the slanted images are corrected with the angle. In experiment we tested a total of 1,500 images of vehicles license plates with 10,299 digits and obtained a digit extraction rate of 95.2 % and a correct digit recognition rate of 97.09 %. Our paper deals mainly with a method to detect digit areas (candidate areas) from natural visions (IR). Although we have tried classifications by a simple template matching we considered only the digit class. To improve the classification ability. We also have to consider the other classes, such as Characters and discriminates the digits from these classes (night vision) infra red images. In addition to further improve the classification power or night vision images, We may have to use more advanced classifiers such as scan lines for the accurate result in the (Night Vision) Infra-Red images. algorithm based on Harris corner detector and PCA is proposed for VLP skew correction. Results Show that the algorithm works very well on positive and negative skewed images and blurred images. Algorithm gives reliable results with very less computation complexity.

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