A Robust Hough Transform Based Method for Direction Detection and Its Application

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Abstract - *Hough Transform (HT) is a widely used method for finding lines, circles and other image features by projecting images onto a parametric space to simplify the feature detection. Direction detection has played an important role in many applications. Various approaches including HT-based methods have been developed for direction detection. Most HT-based methods try first to enhance image line features of an image, and then map the enhanced features onto Hough space to find line(s). In this paper, a new robust method which is based on Hough Transform is proposed. Standard Deviation as a cost function is applied along every angle index in Hough space and it transfers the two-dimensional Hough space into a one-dimensional curve which can reveal the overall directional information in the original image. Its full utilization of statistic information inherent within Hough space makes it sensitive to feature direction and robust to interference caused by bias in Hough space.*

Keywords: *Image object recognition, Hough Transform, Direction detection, Image orientation.*

1 Introduction

An important and frequently occurring problem in digital image processing is the detection of straight lines or direction of texture which can be categorized into line clusters. This kind of problem can be simply illustrated as finding parameter(s) of lines' direction according to a set of candidate points, representing one or more lines, lying on a background.

Rosenfeld [1] described an interesting method proposed first by Hough [2] in which the candidate points are transformed into lines in a slope-intercept parameter space. Its unbounded slope-intercept range complicates the application of this technique. Duda and Hart [3] later improved the Hough technique by using angle-radius (θ-ρ) parameterization instead of the original slope-intercept parameterization that is the HT (Hough Transform) used today.

Duda and Hart's procedure works well with most applications as long as line(s) features exist in the image being analyzed. Some researchers [4], [5], [6] and [7] proposed HT-based methods for direction detection which are based on line(s) detection in which different methods are used to enhance line(s) features, and then map the enhanced results onto Hough space in order to get the wanted θ parameter by localizing line or few lines. Those methods will meet trouble when desired pattern is mixed with strong interference line(s). Many other skew detection methods have been developed. Among them are projection profiles based methods [8-9] which work well in limited angle range, interline cross-correlation [10-11], least square method [12], nearest neighbor search [13-14]. Most of the above algorithms are originally designed for document image skew detection. With different speed and accuracy, they can solve the problem of document skew in a satisfactory way. But they will face problem handling number plate images with perspective distortion (both skew and slant). Interline cross-correlation [10-11] and nearest neighbor search [13-14] methods will fail in this kind of application because normal number plates (See Australia number plate) are only single line with one exception, bicentennial plate, which has two lines of texts and numbers. For least square method [12], its preprocessing will not work properly with number plate images because the text line in a number plate will connect with plate frame due to installation or other reasons that may make its already suffered accuracy problem [15] worse. More important, non of interline cross-correlation, least square or nearest neighbor search methods can properly applied for number plate slant angle detecting that is almost same critical as skew angle because it may seriously influence the next stage character segmentation and recognition. Hough transform can make good usage of the directional information in processed images without reducing processed pixels too much during preprocessing. It can achieve the highest accuracy with trade off of some computational cost.

In this paper, method using Standard Deviation (StdDev) as a cost function is proposed to map the two dimensional Hough space into a one dimensional SD (StdDev) curve. This approach can solve the direction detection problem in a very straightforward and robust way under various conditions.

The rest of this paper is organized as follows. In Section 2, the algorithm of our method is presented. The generalized procedure using this new algorithm is described in Section 3 and experimental results that demonstrate the feasibility and robustness of this algorithm is presented in Section 4. Finally, conclusions are drawn in Section 5 with the future work discussed as well.

2 Methodology

Before explaining our proposed method, it is helpful to have a brief review of traditional Hough Transform proposed by Duda and Hart [3] which is based on polar representation of a line. Such parameterization specifies a straight line by its distance ρ from the origin and the angle θ of it's normal. A line is represented as the points in the set of

$$L_{\theta,\rho} = \{(x, y)| \rho = x\cos(\theta) + y\sin(\theta)\} \qquad (1)$$

where θ falls into [0, π]. The coordinates (x, y) are in a coordinate system with origin O. Point ($N_r/2$, $N_c/2$) is chosen as the origin O of the image where N_r is the total rows of image and N_c is the total columns. θ and ρ are normally both limited to a number of discrete values denoted by N_θ and N_ρ respectively. In this paper, for better illustrating purpose, all examples use the value $N_\theta = 360$ (in practice 180 is enough) and

$$N_\rho = \sqrt{N_r^{\,2} + N_c^{\,2}}\,/2 \qquad (2)$$

N_ρ is not normalized to a fixed value. The letters i and j in the following are used as the indices (called θ and ρ indices) corresponding to θ_i and ρ_j values. H_{ij} represents one cell in the Hough accumulator array. The basic principle of Hough method is that Cell H_{ij} with higher account indicates higher possibility of line existence with parameter θ_i and ρ_j.

Two important properties of Hough Transform have to be emphasized. First, from H_{ij} value, we can find out how many pixels in the Cartesian space vote for this line or lay on this line if Hough transform has been performed on a binary image. However, we are not certain about the distribution pattern of these pixels on their line, and these pixels may appear in a continuous or sporadic manner. This is what one expects from HT because patterns of lines on the original Cartesian space vary greatly due to the endless variety of images. This is why HT is very robust for handling complex images. Another important property of HT is that all cells H_{ij} ($-N_\rho < j < N_\rho$) with same index i represent a cluster of parallel lines. A truth lies behind a HT is that all candidate pixels in the Cartesian space vote once for line clusters at every angle i ($0 < i < N_\theta$). For fixed number of candidate pixels, the stronger the directional features (certain textures or patterns) are in the Cartesian space, the more pixels are located within line cluster that best match the angle of directional feature. In Hough space, cells at that angle reveal bigger variance because votes go mainly to certain lines that best match the dominant directional feature in the original Cartesian space. Now, our method reveals naturally by just one step ahead. We try to find out a criterion or cost function in the ρ − θ space that can expose the variance of cells at each angle and, very importantly, make comparison possible between different angles. Standard deviation (StdDev), a statistic that can tells us how tightly all the various examples are clustered around the mean in a set of data, is chosen as criterion of our method. The above-mentioned property that sums of all cells at individual angles are the same makes the admissibility condition of using the StdDev as the criterion. Hence, we have that,

$$H_\theta = H_i = \sum_{j=-N_\rho}^{N_\rho} H_{ij} \qquad i \in (0, N_\theta) \qquad (3)$$

Therefore

$$\text{mean}_i = \text{mean}_\theta = H_\theta / 2 \times N_\rho \qquad i \in (0, N_\theta) \qquad (4)$$

Then, the cost function is defined as

$$SD_i = \sqrt{\frac{1}{2\times N_\rho}\sum_{j=-N_\rho}^{N_\rho}(H_{ij} - \text{mean}_\theta)^2} \quad i \in (0, N_\theta) \qquad (5)$$

We can find the maximum value (highest peak or local maximum) on the SD_i curve ($0 < i < N_\theta$). The highest peak indicates the dominant direction present in Cartesian space and the local maximums (smaller peaks) represent the directions that are not as significant as the dominant one but still meaningful for some applications. This is illustrated in Fig. 2. The angle corresponding to the secondary peak of SD_i curve can help us perform slant correction.

3 Generalized Procedure

The overall procedure of our method is comparatively simple and straightforward. First, gray level source images are transformed into gradient images if necessary like in the application of number plate correction. The reason for choosing gradient image is that interference from large uniform blocks can be reduced to minimum level. But no more preprocessing is done to enhance line features. Secondly, gradient image are converted to binary image. The general principle of this step is to control the number of candidate pixels, while keeping enough candidate pixels that represent desired features. Thirdly, all candidate pixels are used for HT. Fourthly, each SD_i is calculated according to Equations (3) (4) and (5). Fifthly, peak(s) are searched for identifying the significant direction(s). This generalized method can be modified for various purposes. One of them is for skew and slant correction used in our number plate recognition system, and another one is to be applied for document processing..

4 Expertement

Experiments for testing the feasibility and robustness of our method are conducted by applying the above-mentioned procedure shown in Section 3 on two kinds of images. One is car number plate images which are targeted by the search algorithm shown in [16] and have been isolated from complex backgrounds. Most of the number plates are skewed and slanted due to the instability of our mobile surveillance system, ground surface and relative position between inspected vehicle and camera. About 534 images of this kind have been processed using our algorithm. Another kind of images is scanned documents with pre-set rotation angles. About 100 of them are tested.

Some results are shown in Figs 1 through 5. For better illustrating purpose, Hough images and SD curves are all depicted in a 360° range for a clear illustration of peaks that cross over 180°. In practice, only half is used. In Hough images and SD curves, the x axis is the θ index and the y axis is the ρ index or SD value. Two sample lines are drawn in vertical and horizontal directions in Hough images. The vertical line identifies the θ index i and horizontal sample line identifies the ρ index j. The ρ histogram shows the cells' values on vertical line.

a b c

Fig. 1. Isolated number plate with distortion (a), Gradient image of (a) by applying Sobel operator (b) and Number plate area after skew and slant correction.

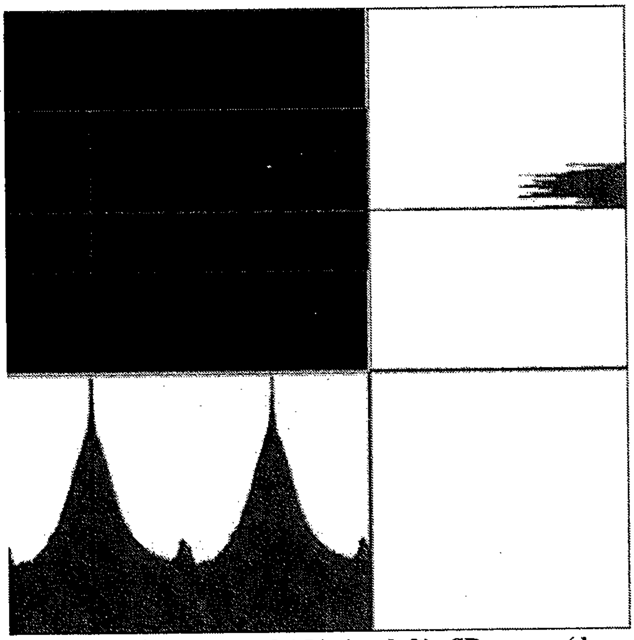

Fig. 2. Hough image of 1(b) (up left), SD curve (down left) and ρ histogram from vertical sample line (upright).

Testing results from images in the first category are very encouraging. Among 534 testing images, only few very poorly focused samples failed for proper slant correction but all of them have been treated through proper skew corrections. Because the skew and slant angles are not preset, the result images are checked through direct measurement. The accuracy for skew correction is measured horizontally by the alignment of lower part of all characters within number plate. The slant correction is measured vertically based on the side edge of the plate. For skew correction, 95.7% are within one pixel and the rest within 2 pixels. If we represent those errors in terms of angle, all errors are within 1°. This is accord with the quantized accuracy of angle index (1° for each cell) in Hough space. The results of slant errors are similar to the skew one except for those few poorly focused images. It is explainable because the blurred images greatly weaken the texture features that we need for detecting slant parameters, and other structure within the analyzed image may overwhelm the desired texture features and become dominant.

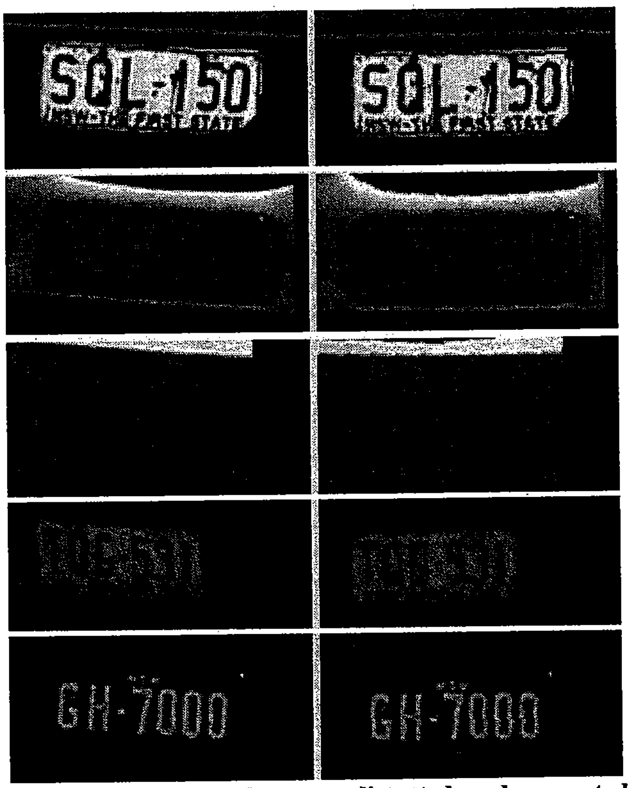

Fig. 3. Comparison between distorted and corrected number plates: Distorted number plate images (left column) and images after correction (right column).

As a whole, these results are satisfactory enough for the segmentation process followed. Figs 1 and 2 illustrate the procedure shown in Section 3 applying to one number plate image. In this example, the dominant direction matches the highest cell count. The second peak indicates the second dominant direction that helps for slant correction. Several samples showing the original images and corrected images are displayed in Fig. 3.

The experiment number plate images before correction and after correction are then both used for character recognition test by third party OCR software named ABBYY fineReader 8.0 Professional Edition. The recognition rate of the number plate as whole for corrected number plate images is 93.6% and 58.3% for uncorrected individually. This result demonstrates a significant improvement in number plate recognition rate after correction compare to the unacceptable recognition rate without correction.

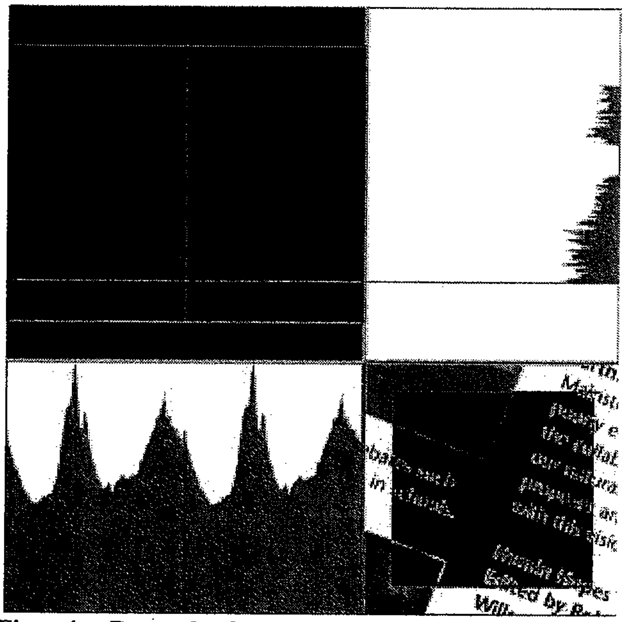

Fig. 4. Rotated document image with graphics (downright), Hough image (up left), SD curve (down left) and ρ histogram from vertical sample line (upright)

Results from experiments using some document images are more illustrative to show the power of our method. All documents under testing have preset rotation angles. The angles detected by our method match perfectly to the preset one. Example in Fig. 4 shows an image containing graphics. Text rotation angle is detected at the highest peak with angle 21° (90°-69°) that is exactly same as the preset one. The second highest peak 159° (69°+90°), which is perpendicular to the dominant one, represents another orientation of text feature. The fourth highest peak matches highest cell count which is identified by the horizontal sample line. It represents interference from one single line which is not parallel to dominant direction. It is a line lying at the very right end of tested image. This strongly supports our claim that our method is robust to interference. This claim is supported again by our next experiment illustrated in Fig. 5. In this testing image, artificial line is introduced across the text. The highest peak represents the desired dominant direction and the second highest one represents the artificial line.

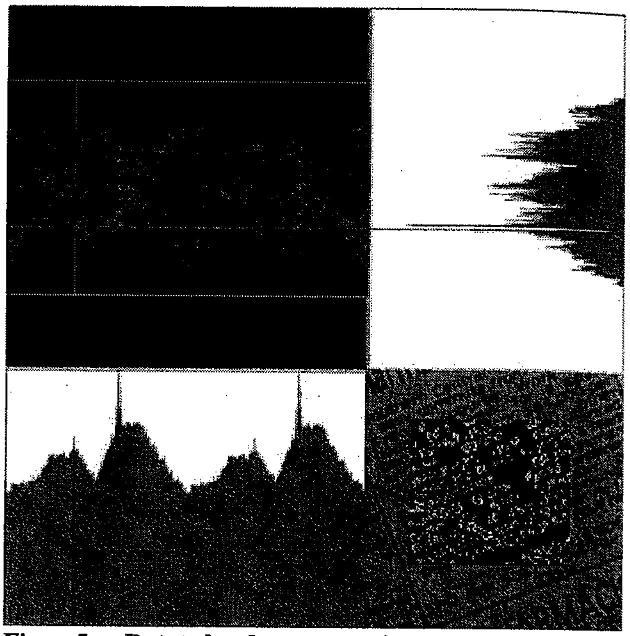

Fig. 5. Rotated document image with strong interference line (downright), Hough image (up left), SD curve (down left) and histogram from vertical sample line (upright).

5 Conclusions and Future Work

Experiments results demonstrate that our new HT based method is capable of finding dominant direction and other significant directions. Due to its two-pass global statistic procedure, one by HT itself and one by our StdDev based method, the new method fully utilize feature information lying in an image. That makes it highly sensitive to direction feature in image and robust to interference. Its accuracy is high enough in handling number plate images that has fewer directional features compare with document images. The processing speed is also acceptable for our system due to relatively small number plate area and rapidly increased PC capacity. Another advantage of our method is straightforward and simple. Most existing methods [4][17] for improving the efficiency of HT in terms of speed and accuracy can still be used together with our method. The advantage of proposed method over other methods [10-14], which include the traditional Hough space based maxima line method, is its capability of detecting not only skew but also slant angle. Proposed method outperforms projection profiles by its unrestricted angle detection ability.

The new method proposed in this paper can not only solve practical problem but also could be useful tool for analysis the property of Hough space. This will be a topic of our future research.

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