High-Accuracy Skew Estimation of Document Images

Chin-Teng Lin, Kan-Wei Fan, Chang-Mao Yeh, Her-Chang Pu, and Fang-Yi Wu

Abstract

This paper presents a new skew angle estimation algorithm for binary document images based on the FCRM (fuzzy c-regression models) clustering method with the aim to resolve the disadvantages of low accuracy and robustness of the existing approaches. This algorithm consists of four processes. The first process transfers the input image into parallel straight lines through image analysis. The second process uses the operating window selection to accelerate the executing time. The following process magnifies the image by fast interpolation to increase the accuracy of skew angle estimation. Finally, the FCRM method is applied to estimate the skew angle. A test set of 184 documents of different kinds is used to measure the performance of the proposed algorithm. Experimental results show that the proposed method has a high precision rate for different document types; it is able to accurately estimate the skew angles that range between –89^o and +89^o.

Keywords: FCRM, cross correlation, run-length smoothing, operating window selection, fast interpolation.

1. Introduction

Converting paper documents into electronic format is now vital for record transmission, management, archiving, retrieval and many other applications, because paper-based office documents occupy considerable space and hardly deal with all kinds of complicated data-mining. The key stages in a document conversion system are scanning, binarization, region segmentation, text recognition, image enhancement, skew estimation and correction. During scanning, the paper may not be fed properly into the scanner by either hand placement or automatic document feeders creating a skew angle in the document image and thus reducing the accuracy of document analysis or OCR. Consequently, skew estimation is a very important stage in document analysis.

Many methods for skew angle estimation have been developed during the last few decades. These methods can be categorized into four types: projection profile [1]-[5], nearest neighbor clustering [6]-[8], Hough transformation [9]-[12], and cross-correlation [13]-[14]. These methods are often efficient, but have many drawbacks affecting the accuracy of the skew angle estimation for actual applications. Postl [1] presented an approach of calculating the projection profiles of the document image in combination with the Fourier transform. The skew angle was then obtained from the density of the Fourier space. Hashizume *et al.* described the nearest neighbors clustering method for the skew estimation [6] and found the nearest neighbors of all connected components. The direction vectors for all such pairs were accumulated in a histogram, and the peak in the histogram gave the dominant skew. These two methods suffered from the restriction of the identifiable angle range. Hinds and Colleagues [9] presented a popular skew estimation methods based on the Hough transform. The gray scale of the burst image was created from the black run lengths perpendicular to the text lines. Then the text lines of the burst image were identified with the Hough transform. Yin [12] enhanced the Hough transform method by smoothing the black runs and locating the black-white transitions to emphasize the text lines. This method had high computational complexity and high cost. Yan [13] presented the interline cross-correlation method to cross-correlate the whole document image. This method also was quite time-consuming for large images, and was not very accurate for document images containing graphs and inner strokes of characters. Most recently, Amin [15] presented another skew estimation method by computing the total number of background pixels within the bounding box of the sub-image that was obtained by rotating the original image with some degree. Then the skew angle was calculated by the product of the total number of background pixels and the rotatory angle of the original image. This skew detection method can work for graphic or image regions that may not exhibit a detectable skew angle (e.g., a regular pentagon or a circle).

This study applies fuzzy c-regression model (FCRM) to improve the skew estimation accuracy. The proposed

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skew angle estimation algorithm consists of four processes. The first process is the image analysis module using run-length smoothing and black-white transition to produce parallel straight lines. The formed line pattern is important in the FCRM-based skew estimation since it shows the distribution of clusters. In the second process, the operating window selection module, the smallest meaningful area from the output image of the image analysis stage is selected to decrease the computational complexity. The obtained image is then sent to the fast interpolation module in the third process to magnify the image to raise the estimation accuracy. A binary image, four times the size of the original operation window, including several parallel lines, is obtained. In the final process, the FCRM clustering algorithm [16], [17] is applied to estimate the skew angle. FCRM is developed to create data from a combination of two or more distinct data generation processes. FCRM categorizes the data in the image into several clusters base on features that are especially apparent in the document, and obtains the skew angle from the cluster parameters. This method has high skew angle estimation accuracy and, since it only operates over a certain region, an acceptable computation time. The performance of the proposed method has been measured by a test set of 184 different documents. The experimental results show that the proposed method can estimate the skew angle of a document with high accuracy.

This paper is organized as follows. In Section 2, the proposed FCRM-based skew estimation algorithm is presented. Section 3 describes the experimental and testing results. Finally, the conclusions are summarized in Section 4.

2. Skew Estimation Method Based on FCRM

The proposed skew angle estimation algorithm consists of four principal modules: an image analysis module, operating window selection module, a fast interpolation module, and a skew angle estimation module. Fig. 1 shows the functional block diagram of the proposed FCRM-based skew angle estimation algorithm. We shall first briefly introduce the FCRM clustering method and then describe the functions and operations of each module in details in this section.

A. *Fuzzy C-Regression Models (FCRM)*

FCRM was developed as a way of allowing data to arise from a combination of two or more distinct data generation processes, which depend on the realization of an unobserved random discrete variable. Let $\mathbf{S} = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_k, y_k), \ldots, (\mathbf{x}_N, y_N)\}$ be a set of data where each independent observation $\mathbf{x}_k \in \mathbf{R}^S$ has a corresponding dependent observation $y_k \in \mathbf{R}^t$. The pair $(\mathbf{x}_k, y_k)$ is a feature vector that represents the k-th object. Therefore, the data are drawn from c different fuzzy c-regression models:

$$y = \mathrm{f}_i(\mathbf{x}_k\ ,\ \beta_i) + \varepsilon_i, \qquad i = 1\ ,\ \cdots\ ,\ c\ , \quad (1)$$

where $\mathbf{x}_k$ belongs to $\{\mathbf{x}_1, \ldots, \mathbf{x}_k, \ldots, \mathbf{x}_N\}$ denotes the k-th data sample and the functions f_i are parameterized by β_i, each ε_i is a random vector with mean vector being zero and c is the number of data points to be partitioned. For getting suitable parameters β_i, the objective functions for a fuzzy c-regression model is defined by

$$J_m(\mathbf{U}\ ,\ \beta_1\ ,\ \cdots\ ,\ \beta_c) = \sum_{k=1}^{N}\sum_{i=1}^{c} u_{ik}^m E_{ik}(\beta_i) \qquad (2)$$

where $m \in (1, \infty)$ is a weighting exponent which determines the fuzziness of the resulting clusters, u_{ik} is the important or weight attached to the extent to which the model valued $\mathrm{f}_i(\mathbf{x}_k, \beta_i)$ matches y_k. C-partitions of S are sets of $(c\times N)$ values $\{u_{ik}\}$ that can be conveniently arrayed as a $(c\times N)$ matrix $\mathbf{U} = \{u_{ik}\}$. Each value of the element u_{ik} in $\mathbf{U}$ is taken as the membership of $(\mathbf{x}_k, y_k)$ in the i th fuzzy subset (cluster) of $\mathbf{S}$. This $(c\times N)$ matrix $\mathbf{U} = \{u_{ik}\}$ with arrayed values $\{u_{ik}\}$ is called a fuzzy c-partition matrix, where $\{u_{ik}\}$ satisfy some or all of the following conditions:

$$0 \le u_{ik} \le 1, \qquad \forall\, i, k \qquad (3)$$

$$\sum_{i=1}^{c} u_{ik} = 1, \qquad k = 1, \cdots, N \qquad (4)$$

and

$$0 < \sum_{k=1}^{N} u_{ik} < N, \qquad \forall\, i = 1, \cdots, c \qquad (5)$$

where (4) means that no empty clusters exist. Let $E_{ik}(\beta_i)$ be a measure of error in a particular model's predicted value. The most common example for such a measure is the squared vector norm that is defined by:

$$E_{ik}(\beta_i) = \| y_k - f_i(\mathbf{x}_k\ ,\ \beta_i)\|^2 \quad i = 1,\ \cdots,\ c \ (6)$$

FCRM offers an effective approach to producing estimates of $\{\beta_1, \ldots, \beta_c\}$, which define the best-fit regression models. The fuzzy c-regression model algorithm is given in [16], [17].

***Fuzzy c-Regression Model Clustering Algorithm* (FCRM)**

Input : image document dataset

$\mathbf{S} = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_k, y_k), \ldots, (\mathbf{x}_N, y_N)\}$.

Output: the parameter set $\{\beta_1, \ldots, \beta_c\}$.

Algorithm:

Establishing an initial fuzzy c-partition matrix. $\mathbf{U}^{(0)}$ satisfying equations (3)-(5).

Set the iteration index $r = 0$.

Set the stop index equal false.
While the stop index=false
{

1. Calculate the restricted function
   minimize $J_m(\mathbf{U}^{(r)}, \beta_1, \ldots, \beta_c)$
   Get the value $\beta_i = \beta_i^{(r)}$ for the c mode
2. Update $\mathbf{U}^{(r)} \rightarrow \mathbf{U}^{(r+1)}$, with $E_{ik}=E_{ik}(\beta_i^{(r)})$ as follows:
   if $I_k = \varnothing$ then $u_{ik} = \dfrac{1}{\sum_{j=1}^{c} (\frac{E_{ik}}{E_{jk}})^{\frac{1}{m-1}}}$
   If $I_k \neq \varnothing$, then u_{ik}=0 for $i \notin I_k$
   $$\sum_{i \in I_k} u_{ik} = 1 \text{ for } i \in I_k$$
   where $I_k=\{i \mid 1 \le i \le c,\ E_{ik} = 0\}$ and $\varnothing$ is empty set. Check for termination in some convenient induced matrix norm.
3. If $\left\| \mathbf{U}^{(r)} - \mathbf{U}^{(r+1)} \right\| \le \varepsilon$ then the stop index=true;
4. set r=r+1

}
output the parameter set $\{\beta_1, \ldots, \beta_c\}$.

B. *FCRM-based Skew Estimation Algorithm*

The proposed skew angle estimation algorithm consists of four processes. First, the image analysis module processes an input image to a uniform document type comprising several parallel straight lines stretching in the same orientation by. The input image is generally limited to documental form containing mainly text information. Then, the operating window selection method is applied to extract a meaningful small area for skew estimation in the operating window selection module to reduce of the computational cost. In the next stage, to increase the estimation accuracy, this image is magnified to four times the original size in the fast interpolation method module. Finally, the image resulting from this process is then sent to the FCRM module, which is the skew estimation system kernel. The FCRM algorithm can precisely estimate the skew angle of the original input image.

The image analysis module uses three procedures: binarization, run-length smoothing, and black-white transition. When an original image enters the proposed system, it is first processed by the image analysis module, not only to identify the document pattern, but also to decrease the input image information for the skew angle estimation step. The input image is required to be in the bitmap format, and can be either RGB or grayscale. The inner strokes of characters, which make estimation of the base lines of text difficult, can be significantly smoothed with a run-length smoothing procedure originally developed for document block segmentation [12] in the image analysis stage. The black pixels are denoted by 1, and the white pixels are denoted by 0. The horizontal run-length smoothing procedure smoothes the horizontal black runs by linking them if the length of their interval white space is shorter than a given threshold. Most inner strokes of characters are smoothed out after applying the smoothing procedure on the document image. Fig. 2(c) illustrates the resulting image after applying the horizontal run-length smoothing procedure in Fig. 2(a). The smoothed image is resample to enhance the base lines and reduce the amount of data, which makes the FCRM computationally expensive. The smoothed image is first scanned vertically column by column to find each black-white transition at the black pixel by retaining its value as 1 and replacing the values of the other black pixels with 0. The resulting image emphasizes the base lines of the text. Fig. 2(d) illustrates the result by locating the black-white transitions vertically on Fig. 2(c). Since the base lines of the text in Fig. 2(d) are more dominant and easily estimated than those in Fig. 2(b), the accuracy of the estimated skew angle is increased. Binarization, run-length smoothing, and black-white transition produce an intermediate image. The intermediate image pattern generally comprises several parallel straight lines stretching in the same orientation. The intermediate image is generated to increase the accuracy of the document skew estimation.

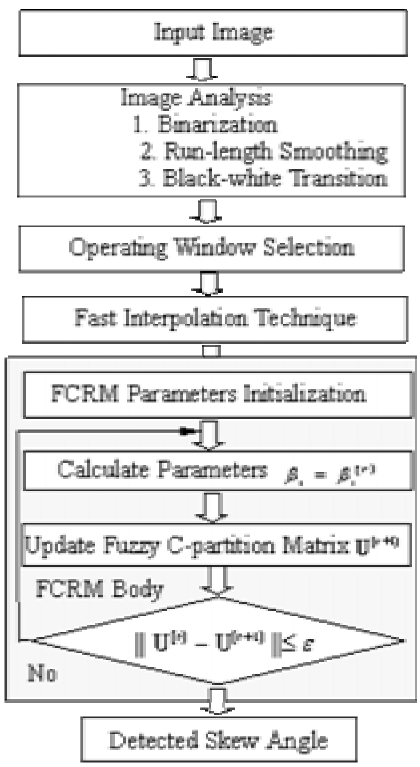


Figure 1. Flowchart of the proposed FCRM-based skew angle estimation method.

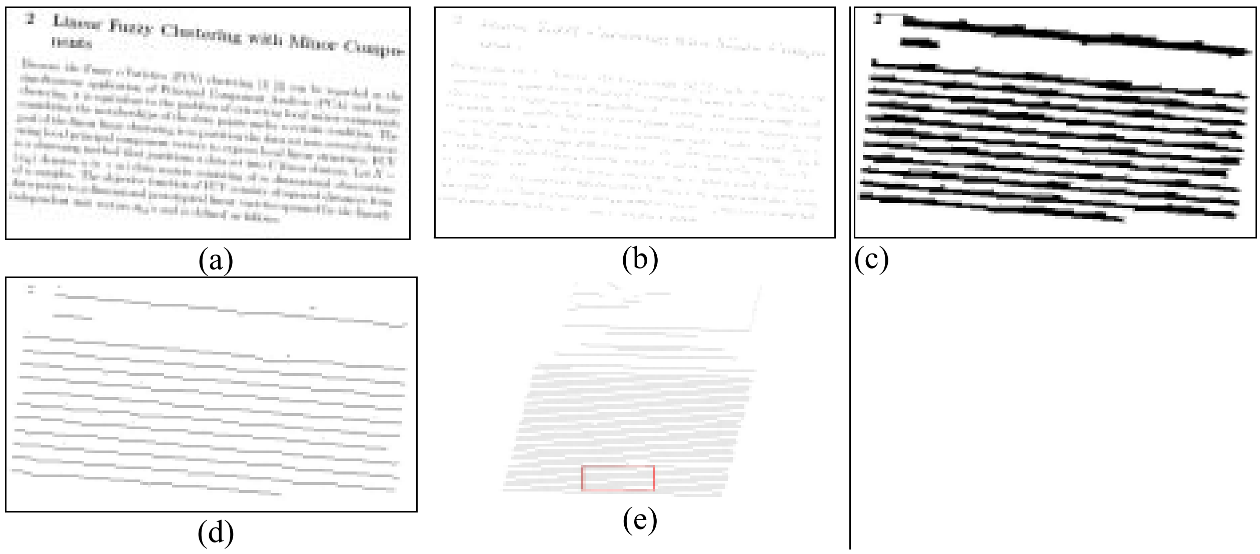


Figure 2. An example illustrating the skew estimation method: (a) the skewed text image; (b) the burst image of (a); (c) the result by applying the horizontal run-length smoothing procedure on (a); and (d) the result by locating the black-white transitions vertically on (c); (e) the operating window selection result.

In selecting the next operating window, an appropriate operation window containing the text region is chosen to decrease the computational time during the process. If the window is too large, then the needless fraction will be obtained, causing in skew estimation errors. If the operation region is too small, then only limited information would be obtained, reducing the accuracy of estimation. To obtain a tradeoff between the sizes of the operation region and the computational cost, the region size is generally quite small, at around 100×100 pixels. Notably, a few text lines are adequate to estimate the skew angle, so using a whole page is not necessary. Because this method can be used in the images being processed with run-length smoothing procedure and black-white transition rather than in original images, this working window selection method will still work very well even with graphics or pictures being reduced to base lines during the earlier preprocessing stages. Fig. 2(e) illustrates the operating window selection result of Fig. 2(c), which has been processed with the run-length smoothing and black-white transition procedures. The selected part illustrated in a red rectangle in Fig. 2(e), with dimensions 100×100 pixels, is centered on the pixel of the maxima of the projections of its horizontal and vertical histograms.

In the next stage, this image is magnified to four times the original size in the fast interpolation method module for increasing the estimation accuracy. Many methods, such as nearest neighbor, linear, quadratic and cubic interpolation functions, can be used in the fast interpolation stage to enhance the image. However, these methods have various flaws, such as blurring of edges, ringing around edges and loss of texture. B-spline methods improve the visual results, but increase the computational cost [18], [19]. A novel and fast algorithm has been used to enhance the resolution of an image by an arbitrary factor based on adaptively selecting different interpolating filters depending on local image analysis [20-24].

The FCRM clustering algorithm is used to estimate the skew angle of an image document, producing many parallel straight lines. When an image enters the FCRM-based skew angle estimation module, the 2-D coordinate of every black pixel is recorded as the input data. These data are categorized into several clusters described with pre-defined models. Set m=2, and c as the number of clusters. The form of clusters is represented with straight line:

$$f_i : y_i = \beta_{i1} + \beta_{i2} x \qquad i = 1, \cdots, c \tag{7}$$

Equation (6) is used to compute the measure of error. The values of the c model parameters $\beta_i = \beta_i^{(r)}$ in Step 2 are computed with equations:

$$\beta_{i1} = ((\sum_{k=1}^{N}(u_{ik})^2)(\sum_{k=1}^{N}(u_{ik})^2 \mathbf{x}_k y_k) - (\sum_{k=1}^{N}(u_{ik})^2 \mathbf{x}_k)(\sum_{k=1}^{N}(u_{ik})^2 y_k)) / K_i \tag{8}$$

$$\beta_{i2} = ((\sum_{k=1}^{N}(u_{ik}\mathbf{x}_k)^2)(\sum_{k=1}^{N}(u_{ik})^2 y_k) - (\sum_{k=1}^{N}(u_{ik})^2 \mathbf{x}_k)(\sum_{k=1}^{N}(u_{ik})^2 \mathbf{x}_k y_k)) / K_i \tag{9}$$

where

$$K_i = \Big(\sum_{k=1}^{N}(u_{ik})^2\Big)\Big(\sum_{k=1}^{N}(u_{ik}\mathbf{x}_k)^2\Big) - \Big(\sum_{k=1}^{N}(u_{ik})^2\mathbf{x}_k\Big)\Big(\sum_{k=1}^{N}(u_{ik})^2\mathbf{x}_k\Big) \quad i=1,\cdots,c \tag{10}$$

The parameters of each mathematic model are iteratively adjusted with the memberships in the fuzzy c-partition matrix. Finally, termination in some convenient matrix norm is checked. If $\|\mathbf{U}^{(r)}-\mathbf{U}^{(r+1)}\| \le \varepsilon$, then the process stops; otherwise, a new iteration is executed.

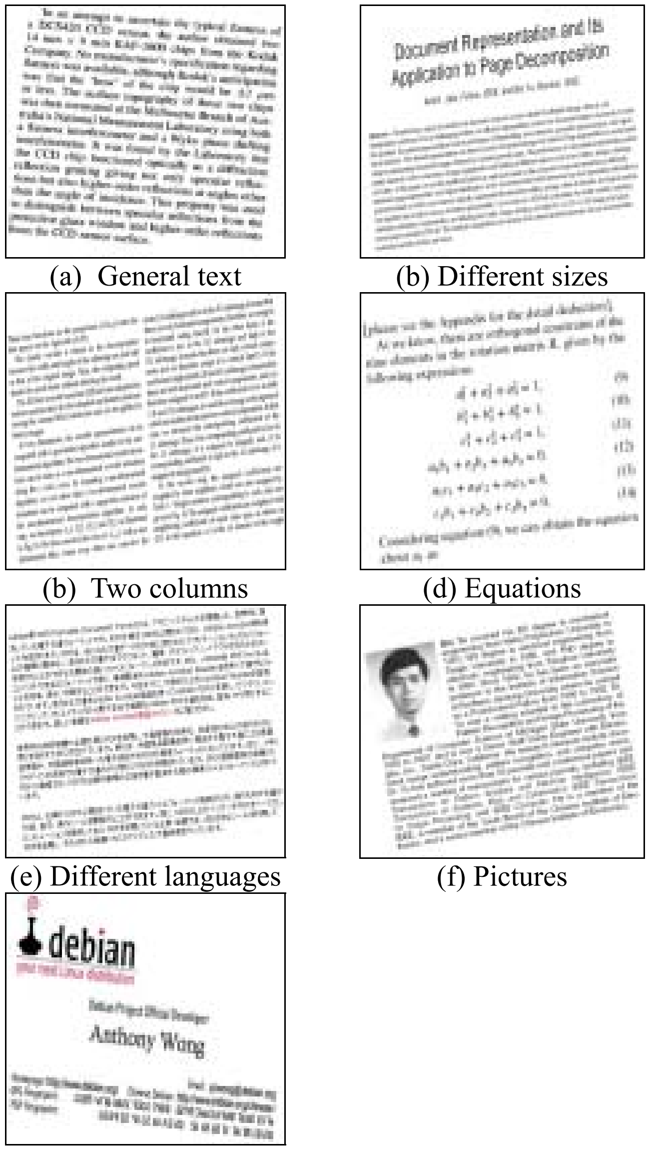
Once the iteration stops, c straight lines are obtained. The parameters β_{i2} for i=1, …, c of the models are equivalent to the slopes of these lines. The arctangent values of parameters β_{i2} are the angles of these lines from the horizontal. The skew angle of the document can be precisely estimated by FCRM algorithm.

3. Experimental Results

The performance of the proposed algorithm was measured on 184 testing documental images obtained by scanning seven different document types including 1) general text, 2) fonts with different sizes, 3) two columns, 4) equations, 5) different languages, 6) pictures, and 7) name cards, such as journal papers and magazines. Fig. 3 illustrates some of the test images. Each type had 23 images, forming the 184 testing images of the image set. The scanning condition is at a resolution of 300 dpi and the color depth is 24 or 8 bits or grayscale skew documents, generated by Adobe Photoshop. The estimation range was set to [-89°, +89°] and the angular resolution was set to 0.1°. Images were tested in every category to measure their performances. The speed was measured in CPU time on a Pentium 1.6GHz PC, and the accuracy was calculated as the difference between the true and estimated skew angles. All of these algorithms were implemented in C language.

Table 1 compares the proposed FCRM-based skew estimation algorithm and the interline cross-correlation method [14]; both the average error and computational time are shown. The accuracy error is given by the difference between the estimated skew angle and the actual skew angle. From Table 1, the FCRM method is more accurate than the interline cross-correlation method. The average errors of the FCRM method are below 0.2° for most documents, clearly demonstrating the high accuracy of FCRM. The computational time of FCRM is much longer than the interline Cross-Correlation method. Because FCRM must calculates the minimum of the objective function repeatedly until the optimal parameters β_i of the fuzzy c-regression mathematical model is found. The interline Cross-Correlation method only calculate the cross correlation function for a binary image. The computational cost of FCRM is higher than the interline Cross-Correlation method. This result is as expected due to the innate character of FCRM, which adjusts the parameters of every mathematic model and thus determines the skew angle. The error rates of both methods increase when testing the name cards because the name cards usually contain less information, which is inadequate for skew angle estimation. Fig. 4 demonstrates the average errors chart for different types of documents. The FCRM method performs the best due to having the smallest accuracy errors for every type of document.

Fig. 5 illustrates the chart about computational time. The average skew estimation computational time of the cross-correlation method is 0.449 seconds since the complexity of the cross-correlation method is much less complex than the FCRM. FCRM has the longer computational time, averaging to 8.414 seconds, but it is acceptable in most cases



(a) General text (b) Different sizes

(b) Two columns (d) Equations

(e) Different languages (f) Pictures

(g) Name card

Figure 3. Samples of testing images.

Table 1. Average error and computational time for different types of documents

Image Type	Cross-Correlation		FCRM	
	Average Error (deg)	Computational Time (sec)	Average Error (deg)	Computational Time (sec)
(1) General Text	0.70	0.428	0.09	13.114
(2) Different Sizes	0.31	0.440	0.12	12.205
(3) Two Columns	0.36	0.447	0.14	10.695
(4) Equations	0.31	0.436	0.29	2.886
(5) Different Languages	0.36	0.469	0.16	5.607
(6) Pictures	0.74	0.509	0.21	11.885
(7) Name Card	0.68	0.412	0.51	3.809
Average	0.5	0.45	0.2	8.59

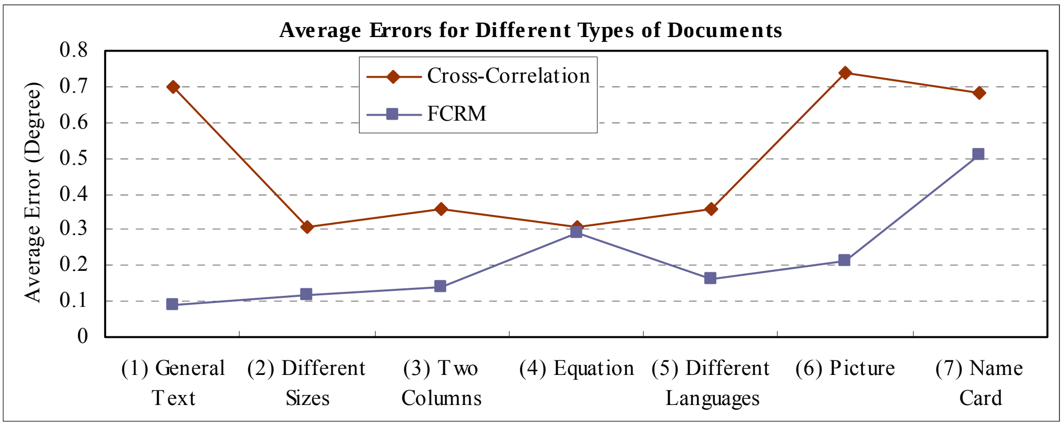


Figure 4. Average errors for different types of documents, where the diamond symbol means the Cross-correlation method and the square symbol means the FCRM method.

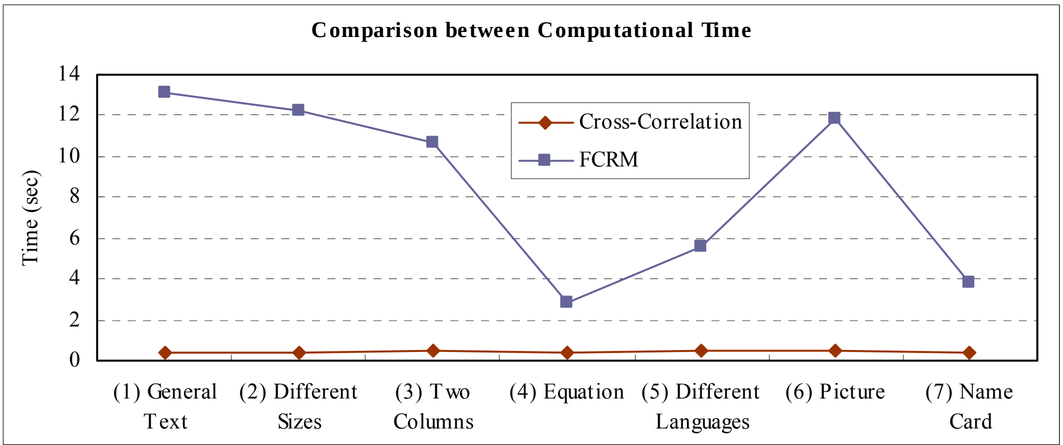


Figure 5. The average computational time for different types of documents, where the diamond symbol means the Cross-correlation method and the square symbol means the FCRM method.

4. Conclusions

This study adopts the fuzzy c-regression algorithm (FCRM) to estimate the skew angles of document images with high accuracy. The experimental results demonstrate that the proposed algorithm has better accuracy than the well-known interline cross-correlation method. The skew estimation is valid for various classes of documents obtained by scanning or copying including general documents, magazines, and newspapers. The system works very well for such input images. The average errors are within 0.2°. The proposed algorithm has a high precision rate for each document type with reasonable computational cost.

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