Halftone structure analysis for classifying print processes

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Abstract

Estimating the source of a printing process is of primary importance for investigative and forensic purposes. This paper deals with development and application of a method for identifying and broadly classifying the print process from a given print sample, especially official forms and certificates. The developed method was not limited only to electrophotographic (EP) method, but was extended to conventional printing methods like offset and gravure. Various methods were previously tested on EP printed samples, but its use on conventional printing methods are being presented for the first time in this paper. A number of features were extracted from the print samples collected, which includes the various halftone structural transformations that inherently becomes a part of the printing process. Also, the halftone dots that forms a part of the image in any printing process were analyzed using Hough transform and the features thus collected were used to form a reference database. The features in this database formed as inputs to a neural network classifier, whereby the classifier was trained to obtain outputs and classify them into EP, offset or gravure classes. Once the trained network was formed newer test print samples were used to extract the same features and fed into the network for classification. The results obtained clearly showed that the outputs were correctly recognized and hence the method presented is quite promising.

Introduction

The necessity to identify the printing process is essential in cases when the origin of the document is to be traced. It plays a pivotal role for document forensics and for tests of questionable documents. Several works has been previously done which leads to methods of document identification and correlating a particular printer to a document. One of the primary and possibly the most commonly used technique is extraction of local features from the image of documents and correlating a set of documents with a previously established database containing feature matrices of a particular printer, when statistical similarities are found, a document is tagged against that particular printer. This approach has its limitations as mostly the methods make use of non-evolutionary algorithms. This paper deals with the same problem but makes use of a more efficient and robust method by utilizing intelligent algorithms of neural networks, which brings very promising results.

The reported literature has used methods to identify and extract features obtained from characteristics intrinsic to the EP printing process [1 – 4]. The quasi-periodic noise that creeps in while printing in EP method is due to imbalance in the optical photoconductor (OPC) drum and the mirror for reflecting beams. So naturally this cannot occur in conventional methods like offset and gravure. But on closer examination, it was revealed, although the cause of the distortion or noise might be different in EP and conventional printing methods, however, there was indeed such distortions occurring in the later. This was mainly due to registration process in the conventional printing methods, where halftone dots of each color gets juxtaposed onto another, creating the full colored images, where dot gain or structural transformation of dots occur.

Many authors have used different techniques for printer identification useful for forensics [5, 6]. The use of geometric distortion signatures as a parameter has been discussed and positive outcomes have been reported [7]. Use of linear features obtained from Hough transform has also showed promising results [8, 9], however, all these methods were applied only to EP printing processes and helped in identification of a specific printer from a given set of printers. But this paper uses the aforesaid techniques to identify the printing process per se and not the printer itself. Use of banding features for identification also has been reported in a previous work [10]. Texture based features has provided very promising results for printer identification [11 – 18].

The paper summarizes two approaches for feature extraction from halftone dots. The first being, the halftone structural elements that occur during the printing processes and the second being the textural features that can be obtained from images of the prints. The structural elements mainly refer to different angle along which halftone dots occur in the four channels viz., CMYK, which can be estimated using Hough transform of the images. The textural features include calculating the various statistical data obtained from the gray-level-co-occurrence matrix (GLCM). On obtaining such features, they were fed into a supervised neural network and were used for training and classification. This trained network was then further used for testing new samples of prints. And the result suggested that the technique used could correctly classify the printing process with a very high accuracy rate. The experiment was conducted across different printing methods and consisted of 900 samples from numerous printers. The novelty of this paper lies in the fact that the presented methods have never been used for classifying print processes, but only for printer models as such. But from the results, it is clear that this technique though has its limitations could well be extended for classifying other classical printing methods along with EP process.

Experimental Design

The work was done by collecting prints from various sources, which included mainly three categories of prints printed with offset, gravure and EP methods. This was followed by scanning them using a HP 1050 multipurpose scanner at 1200 dpi, which rendered good digital image reproduction. The work focused on correlating a particular print with either one of the three classes of print viz., offset, gravure or EP methods. A total of 900 prints were taken, 300 from each of the classes. Once these images were obtained the RGB images were converted first to CMYK color space and then into halftone images and finally binarized using Otsu's thresholding technique [19 – 20].

Once the binarized halftone structure of the images are obtained, Hough transform was adopted. The Hough transform makes use of the parametric equation of a straight line.

$$\rho = x\cos\theta + y\sin\theta \tag{1}$$

ρ represents the perpendicular distance between the origin and the line in consideration. And θ represents the angle between the perpendicular lines to the x axis. These values are stored in an accumulator cell. The accumulator increases for every non-

are the lines that has been mentioned earlier. Histograms are plotted in the figure from which statistical features are being extracted.

The halftone structure being analyzed, the texture features were then extracted from the images. The method used in this work is
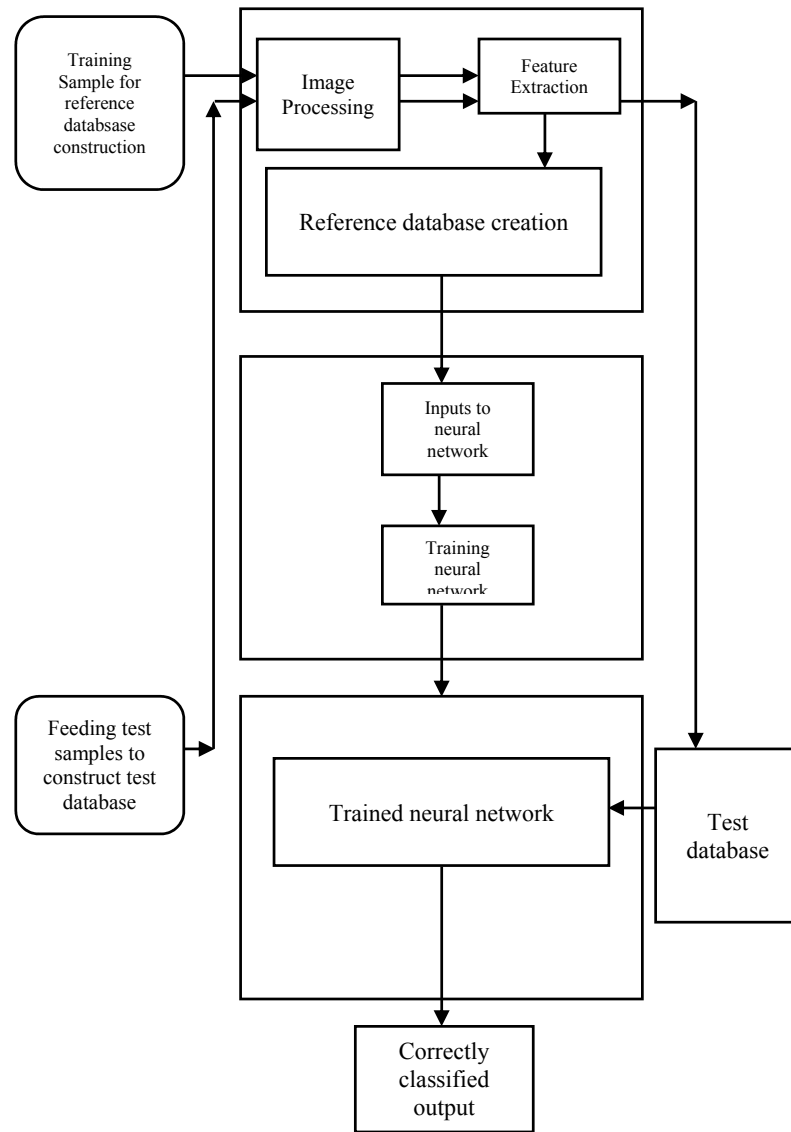

**Figure 1:** *Schematic of the proposed work*

background pixel in the image. Peak values in this cell represents a line. A histogram containing accumulating angle values is created. This was followed by normalizing the histograms

$$P(b) = \frac{N(b)}{M} \qquad (2)$$

where M represents the total number of pixels in the image, $N(b)$ represents the conventional histogram. The various statistical features, including mean, variance, skewness, kurtosis were obtained from the histogram is used as an input to the neural network. Figure represents the Hough transform of various halftone images and the edges being identified by the method. These edges

statistical texture feature extraction which are calculated from a combined intensity levels relative to one another for an image. Depending on the number of intensity points or pixels the statistics can be classified into first order, second order and higher order.

One such method is the Gray Level Co-occurrence Matrix (GLCM), which derives second order statistical texture features. It measures the frequency of occurrence pair of pixels with similar intensity values and bearing a spatial relationship. A GLCM consists of a matrix whose number of rows and columns are equal to that of the number of gray levels G for the image. The matrix element $I(i,j |\Delta x,\Delta y)$ is the relative frequency with which two pixels, speared by a pixel distance $(\Delta x, \Delta y)$, occurring in a neighborhood with two intensity levels are i and j. For a given $M \ x \ N$ neighborhood
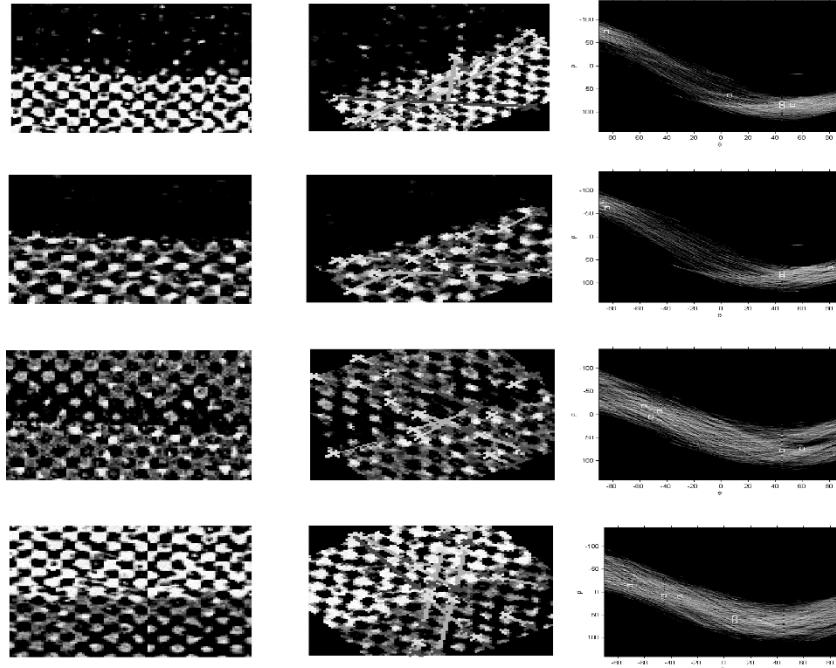
Figure 2: *(left) halftone images, (centre) hough lines of the corresponding images, (right) Hough transform results.*

containing G gray levels from 0 to $G - 1$, $f(m,n)$ is the intensity at sample m, line n of the neighborhood. Then

$$I(i,j|\Delta x, \Delta y) = WQ(i,j|\Delta x, \Delta y) \tag{3}$$

where

$$W = \frac{1}{(M-\Delta x)(N-\Delta y)} \tag{4}$$

$$Q(i,j|\Delta x, \Delta y) = \sum_{n=1}^{N-\Delta y} \sum_{m=1}^{M-\Delta x} A \tag{5}$$

and

$$A = \begin{Bmatrix} 1 \; if \; f(m,n) = i \; and \; f(m+\Delta x, n+\Delta y) = j \\ 0 \; elsewere \end{Bmatrix} \tag{6}$$

The features that were extracted from the GLCM are provided as follows

$$Contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G} \sum_{j=1}^{G} I(i,j) \right\}, |i-j| = n \tag{7}$$

This contrast value will primarily measure contributions from $I(I,j)$ away from the diagonal for $i \neq j$.

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{ixj\}X\,I(i,j)-\{\mu_x-\mu_y\}}{\sigma_x-\sigma_y} \tag{8}$$

Correlation measures the gray level linear dependence between the pixels a particular region relative to each other.

$$Energy = \sum_{i,j} I(i,j)^2 \tag{9}$$

Energy measures the local homogeneity and represents the uniformity of the texture.

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} I(i,j) \tag{10}$$

Once the features were obtained from the images, these together with previously obtained from Hough transform were fed as inputs to a neural network. The neural network served as a classifier. A multilayer perceptron artificial neural network was used as segmentation of images [21 – 23]. There is a single hidden layer and the features are fed as the network input and three output neurons based on three print classes. The network is trained using backpropagation training method, that reduces the mean square error between targets and outputs [24 – 25]. The input consisted of an 8 X 900 matrix which meant for each of the 900 samples a total of 8 features were used as classifying input viz., statistical data from histogram of peak angles from Hough transform, i.e., mean, variance, skewness, kurtosis and the four second order statistical features from GLCM i.e., contrast, correlation, energy and homogeneity. The samples were equally spaced as is evident from the number of samples selected. The number of neurons determines the processing cost, with lesser neurons, there is always a risk of false-classifications but with higher number of neurons there might be the problem of over-fitting. The numbers of neurons were determined empirically, the general thumb rule is,

$$X = \sqrt{M \times N} \tag{11}$$

where X is the number of neurons the hidden layer and M and N that in the input and output layers respectively.

As stated before, the standard performance of a perceptron lies in the fact of reducing the means square errors, in case of a supervised learning algorithm, let us consider the following,

$$\{p_1,t_1\},\{p_2,t_2\},\ldots,\{p_n,t_n\} \tag{12}$$

using the aforesaid feature based identification techniques. The rate of classification was high as has been provided below, at a performance of 96.45 %, the network performed well in terms of classifying the data correctly.
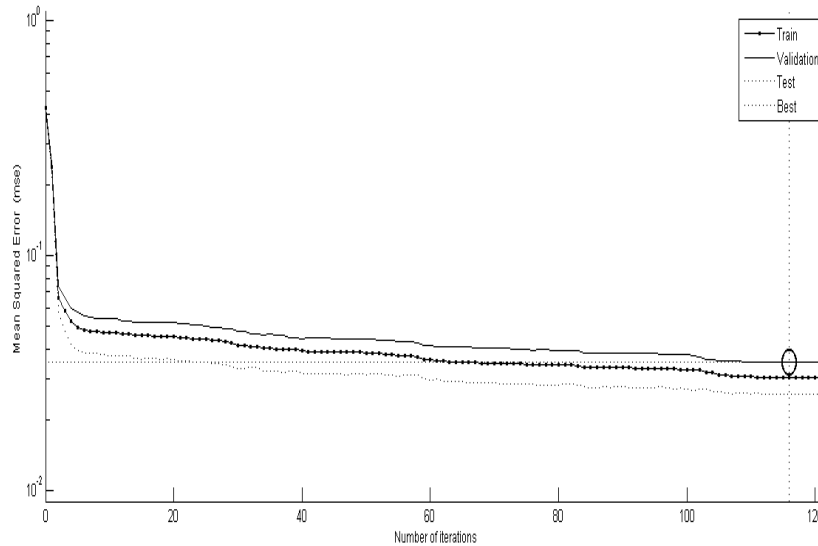

Figure 3: *Mean squared error plot for number of iterations*

where p_1 and t_q are the input and target provide to the network. The error after each input is the difference between the outputs to the target. It can be expressed as follows, where t (k) is the target and α (k) is the output from the network,

$$mse = \frac{1}{Q}\sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q}\sum_{k=1}^{Q}\big(t(k) - \alpha(k)\big)^2 \tag{13}$$

Experimental Data

The provided method was tested on 900 images, of which 300 images each were from a particular class of printing method viz., offset, gravure and EP. The images obtained by scanning them were first converted into CMYK color space and separated into respective channels and then binarized using Otsu's thresholding technique. These images were used for line detection using Hough transform. Figure 2 shows the original images along with the lines and Hough transformed images. Once the image histograms were created by using angles of significant lines in the images, various statistical features were extracted from the images, which served as features for classification.

The above features together with the GLCM features were used as inputs to the neural network. Of the 900 samples, data obtained from 630 (70 %) samples were used for training and 135 samples each were used for testing and validating the network. Multiple trainings were given to the network to identify the least mean squared error value points where best results could be obtained. Table1shows the confusion matrix for the trained and validated network and figure 3 shows the performance of the network with increasing number of iterations. As is evident from the data, the rate of classification was satisfactory and it can be safely stated that the method performed well for classifying prints into three categories

Table 1: Combined confusion matrix from the trained network

Class 1 (Offset)	290	9	1
	96.67%	3 %	0.33 %
Class 2 (Gravure)	10	285	5
	3.33 %	95 %	1.67 %
Class 3 (EP)	2	5	293
	0.67 %	1.67 %	97.67 %

Conclusions

This work provides a novel approach towards solving the problem of identification of prints obtained from different sources. Previous works have suggested methods for the same, but the methods provided in this work are robust in terms of approach as it uses an evolutionary technique for classifying various print processes. The results obtained from work are extremely promising. The rate of correctly classified prints suggests that feature extraction based techniques for classifying prints from classical methods of printing and that of electrophotographic processes is a promising method. Features obtained from histogram analysis from Hough transform of images and that obtained from GLCM served as inputs to a neural network based classifier which was trained and validated. The trained network was tested with some test data and it performed satisfactorily well. Further work could include incorporating various other features like those obtained from wavelet decomposition, which could further increase classification rates.

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