A Matching Process of Handwriting between Exhibit and Specimen

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Abstract

In this paper we present a matching process of handwriting between exhibits and specimen of Myanmar handwriting documents. This is also a method to identify the writer of Myanmar handwriting documents. Many methods have been reported for handwriting-based writer identification. Most such techniques assume that the written text is fixed. There are many methods for writer identification or signature verification. They are the kinds of content dependent identification methods. But our method is a content independent method. In our method, we take the handwriting as an image containing some special texture, and writer identification is regarded as texture identification. We apply the well-established multi-channel Gabor filtering technique to extract features and a Weighted Euclidean Distance classifier to fulfill identification task. The result of this paper will confirm whether handwriting of specimen is the true writer of the exhibit.

Keywords: preprocessing, texture analysis

1. Introduction

Handwriting identification is an active research topic in the computer vision and pattern recognition field [12,15]. Handwriting identification is a behavioral biometric identification approach. There are two types of biometric features: physiological (e.g. face, iris pattern and fingerprint) and behavioral (e.g. voice and handwriting). Handwriting is easy to obtain and different people have different handwritings. Handwriting identification has a wide variety of potential application, from security, forensics, and financial activities to archeology. Since the purpose of handwriting identification is to identify the writer of a specific handwriting, one does not need to know what the written text is. The key point is using texture analysis to extract features. This is a content independent method and requires no segmentation or connected component analysis. A block of handwriting is seen as having a specific texture. The spatial frequency and orientation contents represent the feature of each texture. It is these texture features that we use to identify writers of handwritings. There are many available filters in the multi-channel technique. We use the well-established multi-channel Gabor filters to extract these features. It has demonstrated good performance in texture discrimination and segmentation [1, 13]. And they have proven to be successful in extracting features for similar applications [5, 11, 14, 18, 19]. The new algorithm has been proven to have good performance in English handwriting identification. This paper is to explore its efficiency in Myanmar handwriting identification.

Research into writer identification has been focused on two streams, off-line and on-line writer identification. This paper focuses on the off-line identification. Off-line systems are based on the use of computer image processing and pattern recognition techniques. It is further subdivided into two parts Text dependent and Text Independent We are working on the former one, as that is the more general case. This approach is called Texture Analysis Techniques. Similar work has been proposed by Kuckuck [7], where a Fourier transform technique is used.

Handwriting is one of the easiest and natural ways of communication between humans and computers. Signature verification has been an active research topic for several decades in the image processing and signature verification remains a challenging issue. It provides a way of identifying the writer of a piece of handwriting in order to verify the claimed identity in security and related applications. For example the identification of the writer of archived handwritten documents, crime suspect, and identification in forensic science, etc. In this application, professional handwriting examiners often identify the writer of a piece of handwriting. Although human intervention in the text independent writer identification has been effective, it is costly and prone to fatigue. This task is much more difficult and useful than signature verification [6].

Texture analysis has a wide range of applications. Millions of digital images are created throughout the World Wide Web, digital cameras, different kinds of sensors, medical scanners etc. Image analysis is based on three main image features: color, shape and texture. Texture plays an important role in human vision.

Texture has been found to provide cues to scene depth and surface orientation. Researchers also tend to relate texture elements of varying size to a reasonable 3-D surface. Although textured image analysis has been a topic of research for the last few decades [2,9], due to the complexity and the lack of ability to clearly define the significant features of texture, a number of challenging problems still need to be addressed. Features that have been used to describe texture images include simple mean and standard deviation, Gabor transforms, wavelet-based features, and Fourier transform based features [8,20].

This paper is structured as follows. In Section 2, we presents over all design of the system. In Section 3, we will discuss pre processing in detail. Section 4 will introduce the multi-channel Gabor filters for texture feature extraction. Section 5 describes the classifier applied in this work. Section 6 reports the current status and future work. Finally, Section 7 presents our conclusion.

2. Handwriting Identification

The problem of handwriting identification is a problem of pattern recognition. The overall system of handwriting identification system is illustrated in Figure 1.

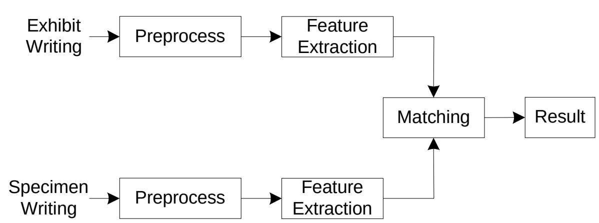

Figure 1. The Flow Chat of the design

The original image is preprocessed to form a uniform block of text. The multi-channel Gabor filtering technique is used to extract features from the uniform text blocks (i.e. the texture images). A Weight Euclidean Classifier is used to identify the writers.

3. Preprocessing

The input is a binary image. The handwriting may contain lines of different point sizes and different spacing between lines, words and characters. Texture analysis cannot be applied directory to input handwriting images, as texture is affected by different word spacing, varying line spacing etc. So for texture feature extraction, the input documents need to be normalized to create a uniform block of text. Before doing normalization we first have to remove the noise from the images. For this we apply the Salt and Pepper filter to remove the noise. After applying this we will get the noise free image. Then further processing will be done on this image.

3.1 Straight Underline Removal

The algorithm for removing straight lines is described below:

1. For each row of the word image, examine each run of continuous foreground pixels (black pixels).
2. Note the length of each run.
3. IF a particular run is greater than half of the actual word length THEN
   A straight underline has been found
4. Store the x-coordinates of the start and end column of the line
5. The underline's stroke width is examined by measuring the length of vertical runs of foreground pixels in each column between the two stored x-coordinates.
6. IF the length of a continuous run of foreground pixels in the above-mentioned area is smaller than or equal to the average stroke width
   THEN
      All pixels in that run are converted to background pixels.
   ELSE
      The foreground pixels remain unchanged

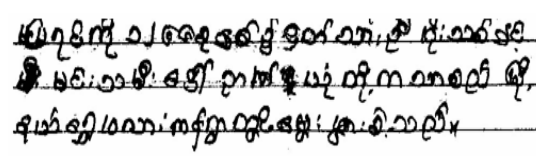

Figure 2. Handwriting Image with underline

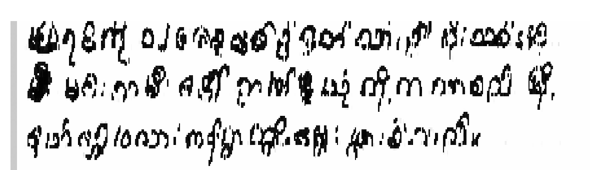

Figure 3. Handwriting Image after removal of straight underline

3.2 Locate text lines

The horizontal projection profile (HPP) of the document is computed.

- Construct Histogram of black pixels against rows
- Smooth the histogram by applying median filter
- The smoothening is performed for different window size (5-21) of the median filter and the one giving least standard deviation for line width is chosen
- Find peaks in the histogram. This corresponds to approximately the center of a line of text.
- Find the points with maximum radius of curvature on both sides of the peaks. This corresponds to the top and bottom of a line of text

The valley between peaks corresponds to the blank between text lines.

3.3 Text lines Normalization

The size of text line may differ in the handwriting documents, so it is necessary to resize each character to the similar size. Given that the height of each line is known, it can easily be scaled.

3.4 Spacing Normalization

The handwriting image may contain different spaces between characters, words and text lines. Different spacing may influence the texture of the images, so the normalization of space is necessary. We normalize the spacing by scaling them to a predefined width

3.5 Text padding

Padding is also required; as this will also affect the feature set. The input image may contain incomplete lines; they are padded with text taken from the start of the line. We will choose the random non-overlapping blocks from this pre-processed page from which the features will be extracted. We are choosing the randomize page as to improve the performance. After this step we will got an image wit the specified spacing between lines and words and with the appropriate padding. In our case, the text will pad to create a block of a predefined size.

4. Feature Extraction

In principle, any texture analysis technique such as the multi-channel Gabor filtering or the gray level co-occurrence technique can be applied to extract features from each uniform block of handwriting. Here we will implement Gabor Filtering. Because experiments showed that Gabor Filtering has better performance [10,16]. In our method, we take a handwriting image as having a specific texture. By using the multi-channel Gabor filtering technique, we can fully analyze handwriting texture in different scales.

4.1 Gabor filter

The multi channel Gabor filtering technique is inspired by the psychophysical findings that the processing of pictorial information in the human visual cortex involves a set of parallel and quasi independent mechanisms or cortical channels which can be modeled by bandpass filters. The multi-channel Gabor filtering approach has been shown to be practically useful for analyzing textured images [4]. Gabor filters can represent signals in both the frequency and time domains with minimum uncertainty [3] and have been widely used for texture analysis and segmentation [5].

In our application, we use pairs of isotropic Gabor filters with quadrature phase relationship [17]. The computational models of such 2-D Gabor filters are (h_e and h_o denote the even- and odd- symmetrical Gabor filters respectively):

$$h_e(x,y) = g(x,y).\cos\left[2\pi f\left(x\cos\theta + y\sin\theta\right)\right]$$
$$h_o(x,y) = g(x,y).\sin\left[2\pi f\left(x\cos\theta + y\sin\theta\right)\right] \quad (1)$$

where *g (x, y)* is an isotropic Gaussian function given by

$$g(x,y) = \frac{1}{2\pi\sigma^2}\exp\left[-\frac{x^2+y^2}{2\sigma^2}\right] \quad (2)$$

The spatial frequency responses of the Gabor function are:

$$H_e(u,v) = \frac{\left[H_1(u,v) + H_2(u,v)\right]}{2}$$
$$H_o(u,v) = \frac{\left[H_1(u,v) - H_2(u,v)\right]}{2j} \quad (3)$$

where ($j = \sqrt{-1}$) and

$$H_1(u,v) = \exp\left\{-2\pi^2\sigma^2\left[(u - f\cos\theta)^2 + (v - f\sin\theta)^2\right]\right\}$$
$$H_2(u,v) = \exp\left\{-2\pi^2\sigma^2\left[(u + f\cos\theta)^2 + (v + f\sin\theta)^2\right]\right\} \quad (4)$$

f, θ and σ are spatial frequency, orientation and space constant of the Gabor envelope.

Figure 4 illustrates the frequency response of an even- symmetric Gabor filter. The orientation θ parameter corresponds to the angle from the u-axis to the center of the Gaussians. The central frequency f corresponds to the distance from the center of the Gaussians to the origin. σ is the space constant of the Gabor filter[21].

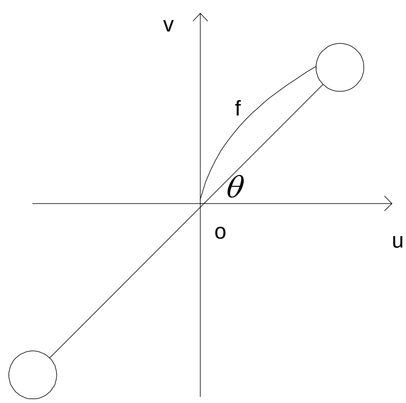

Figure 4. Frequency Response of the Gabor Filter

4.2 Filter design

Each pair of the Gabor filters is tuned to a specific band of spatial frequency and orientation. There are some important regards in selecting the channel parameter f, θ and σ. Experiments show that there is no need to uniformly cover the entire frequency plane so far as texture recognition is concerned [4]. Since the Gabor filters we use are of central symmetry in the frequency domain, only half of the frequency plane is needed. Four values of orientation θ are used: 0°, 45°, 90°, 135°. For each orientation, central frequencies are chosen so that they are 1 octave apart. In order to achieve good results, for an image of size $N \times N$, central frequencies are chosen within cycles/image. Finer selection may be employed in other applications. In our experiments, the input image is of size 128×128. For each orientation θ, we select 4, 8, 16 and 32 as spatial frequencies. This gives a total of 16 Gabor channels (4 orientations combined with 4 frequencies). The above choice is sufficient to discriminate different fonts. The spatial constants σ of these channels, which determine the channel bandwidths, are chosen to be inversely proportional to the central frequencies of the channels [4].

The mean values (M) and the standard deviations (S) of the channel output images are chosen to represent texture features. Thus a total of 32 features per input image are extracted from a given image. They form a 32-dimensional feature vector. Figure 5 shows the flow chart of feature extraction using the multi-channel Gabor filtering technique [21].

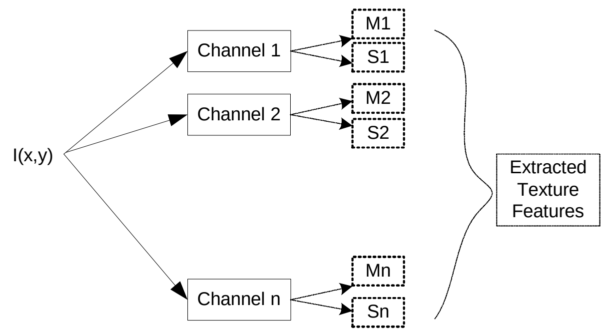

Figure 5. Gabor Filter based feature extraction

5. Classifier

The identification of writers based on given feature vectors is a typical pattern recognition problem. In principle, we can use any type of classifiers here. For simplicity, we may use the Weighted Euclidean Distance (WED) classifier to identify the writer. Features of unknown testing writers are compared with those of a set of known writers. The writer of a handwriting document is identified as writer k *if* the following weighted Euclidean distance is a minimum at k:

$$WED(k) = \sum_{i=1}^{N} \frac{\left(f_{i-} f_i^{(k)}\right)^2}{\left(\delta_i^{(k)}\right)^2}$$

where f_i denotes the i th feature of an unknown handwriting, $f_i^{(k)}$ and $\delta_i^{(k)}$ denotes the i th feature and its standard deviation of handwriting by writer k, N denotes the total number of features extracted from a single writer.

6. Current status and Future work

A number of experiments may be carried out to test our algorithm. A few persons' handwritings may be trained and tested. Myanmar characters was scanned both from exhibit and specimen documents to a 2-colored bitmap image with the resolution of 100 dpi. Each sub-image was preprocessed to form a noise free uniform block of text. And then we may find the mean values (M) and the standard deviations (S) of the channel output images for feature extraction and writer identification. Different combinations of features may be tested. It is needed to achieve highest accuracy and good result.

7. Conclusion

We may present a new algorithm for a matching process of Handwriting between Exhibit and Specimen of Myanmar Handwriting Identification. Different to most existing methods, our algorithm is text independent. The key point is using texture analysis to extract features. In this paper, we have investigated the feasibility of this method in Myanmar Handwriting. The method proposed in this paper is unlike signature verification, this method is content independent. The method needs neither segmentation nor connected component analysis. In theory, any texture classification and analysis technique (such as Gabor filtering and GLCM) can be applied in our method. The method needs no complex computing. It may easily be applied in practical applications. All of these demonstrate that the new method may be able to handle writer identification tasks efficiently.

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