Rotation and Size Tolerant Feature Set for Static Off-line Signature Identification Technique

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Abstract: Use of automated signature verification systems is getting popular due to frequent use of signatures for personal identity in banks etc. Dynamic signature identification techniques have been explored and implemented by a number of researchers for signatures that are input to the system through digitizer gadgets. Nevertheless identification of static handwritten signatures is lacking researchers' attention. A novel technique of handwritten off-line static signature identification is presented in this paper which tolerates fault in signature like variation in size and rotation of the signature. The technique uses discriminative features of signatures based of geometric properties represented by pixel density of annular regions of normalized binary image of signatures. We used 2 to 5 signature samples of thirty authors to train our system which was then evaluated with test signature samples. Test samples were made varying in size and rotation. The false recognition rate of our system was 35%, 22%, 20% and 15% for training sample count to be 2, 3, 4 and 5, respectively. Our system tolerated appreciable variation in size and rotation of test signature samples.

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1. Introduction

Frequent use of handwritten signatures in daily life has ensued active research in the field of signature recognition. Many systems are operative to handle transactions through automatic verification of signatures [1]. Most of the research focuses on on-line signature recognition. This paper presents work on off-line static signature recognition. A technique to extract discriminative features from static image of signature is proposed that imparts tolerance to the signature recognition system against variation in size, rotation and pen type used for system training signature samples and testing signature sample. Our system withstood these variations and exhibited accuracy up to 85%. The following section describes background knowledge of image processing and pattern matching involved followed by proposed technique in section 3. Section 4 explains experiment setup to evaluate the proposed technique where results are discussed in section 5. Conclusions then follow in section 6.

2. Background Knowledge

Characterizing a person with his or her handwritten signatures falls under a large title called Biometrics. The biometric identification of a person does not require password and PIN--personal identification numbers which may be forgotten, lost or stolen. Thus authentication with biometric based systems is receiving greater interest. Hence real-time identification using face, iris, and fingerprint biometric matching is getting popular day by day. Other biometric systems make use of retinal scan, speech, signatures, and hand geometry. A typical biometric system consists of five integrated components:

- A **sensor** device to collect the data and convert it to digital form.
- **Signal processing algorithms** that control quality of activities that develop the biometric template.
- A **database component** that stores information of biometric templates to be compared to for identification.
- A **pattern matching algorithm** that compares the new biometric template with one or more templates kept in the database.
- A **decision process** uses the results from the matching component to make a system-level decision.

Off-line signature recognition systems first digitize the signature image captured through a scanner or a camera and store for later processing. The images thus obtained are called static images.

Features are extracted from the stored images. Off-line signature recognition systems are useful in the situations where only hard copies of the signatures are available on the documents to be authenticated [1].

On-line signature recognition systems capture information when the signature is being signed with a special pen on an electronic surface such as a digitizer combined with a liquid crystal display [2]. The information about the signature thus captured consists of the two dimensional coordinates, the pen pressure, the pen angle and direction.

The captured images of signatures are preprocessed to remove noise and normalize them like centering the signature in the stored images. After that selected features are extracted from the normalized signature images that discriminatively represent the personalized signatures. Different pattern recognition techniques [3] have been used to tackle signature recognition task using the stored extracted features of signatures. These techniques include minimum distance classifiers [4], dynamic programming [5], neural networks [6] and Hidden Markov Models [7, 8]. The accuracy of a biometric system is described in terms of 'false accept rate' (FAR) to relate how many imposters are accepted, and 'false rejection rate' (FRR) to describe how many authorized users are rejected by the system.

Signatures are essentially patterns of line and curve strokes that describe them. These descriptors or features that characterize a signature pattern are processed to model it and later identify or verify it. Features are of two types: the internal and external features. The internal features relate to the interior pixel data of segments of the object image. The external features represent the pixel data of the boundary lines of the segments. Together the features of the image represent the structure aspects of the object image under investigation. Object having common features are assigned an identity class by some processes on the pattern images from image processing. The classes of the patterns are stored in the database for future reference. Any new pattern countered can be recognized to belong to an existing class or a new class to be introduced to the database.

The features of a pattern bitmap include the size of the pattern, the slope of different segments of the pattern etc. These pattern features may be numerical or symbolic, or both. A set of quantitative features extracted computationally is represented feature vector**.** Pattern matching techniques based on decision functions determine the class of the pattern. The number of decision functions in any pattern recognition system depends upon the number of pattern classes. For example, if there are *K* number of classes then there should be *K* decision functions [9]. Before pattern recognition discriminative feature sets of signature must be extracted through signature image processing.

2.1. Preprocessing of Signatures Images

Noise removal is the first step followed by signature centering in the image rectangle. A two dimensional digital image **a**(m,n) of size *M* x *N* is a matrix of values of amplitude **a** in a discrete space**,** defined at the +ive integral values of coordinates m, n where *M* is the number of rows and *N* is the number of columns. The elements of the matrix represent the picture elements of the digital image In case of binary image there will be only two intensity levels; 0 for black and 1 for white pixels, respectively [1-11]. Noise removal uses adjacency properties of pixels defined by neighborhood. Any two pixels having the same grey level in the binary image are connected to form regions and boundaries if they are neighbors to each other.

The processing of image for feature extraction is performed normally in two domains; spatial domain and frequency domain [9]. The term spatial domain refers to the aggregate of pixels properties of the image. Those methods which directly operate upon these pixels are called spatial domain methods. These methods are represented by the transfer functions as below:

$$g(x, y) = T\,[f(x, y)]$$

where f (x, y) is the input image and g (x, y) is the output image. This output image may be a set of features or attributes of the image. This set of attributes may be used for reference as well as testing information of the image. In frequency domain a digital image is usually defined by the values of 'Fourier transform' and its frequency variables [9]. An image is decomposed into its sine and cosine components after the Fourier transform. Every point in the frequency domain represents a particular frequency present in the spatial domain.

2.2. Pattern Recognition Approaches

The scanned images of the signatures are processed to create white background to extract general features [10, 11] like gray shade, texture, shape or context of the image. Further image processing algorithms use this information [10-11] to build more efficient representations for the signatures. Clustering concept is used to find patterns of the targeted classes in the form of vectors of real numbers. Minimum Distance Classification is frequently used in signature recognition system. Multi-dimensional distance is computed between test signature and each registered signatures to identify the minimum distance bearing signature class from the database.

An artificial neural network (ANN) has been used in signature recognition. Capabilities, like self-organization, fault-tolerance and adaptive learning are key advantages of neural networks. However,back-propagation algorithm based ANNs fall to local minima during training. Other issues include architecture selection, feature representation, learning speed, modularity and scaling.

3. Proposed Technique for Discriminative Feature Extraction

Our system for recognition of static off-line signature is based on geometric feature set that impart tolerance to size and rotation variation present in test signatures to the system. After getting the signature centered image, a rectangular outline is drawn around the signature image so that the center of the rectangle coincides with that of the signature image. Because signatures of a person have approximately similar geometry about their centers, so the useful features of the signatures are extracted by using this similarity characteristic. The geometry of the signatures remains approximately similar under different circumstances like; signing with different pens at different times, signing in different sizes, writing at different orientations, etc. This invariant attribute of a handwritten signature is used to implement this signature recognition system. In our signature recognition system, the pixel data is extracted from the annular regions of the signature images. These annular regions are selected in such a way that they have equal width as well as coincident with the center of the signature images. The width of the annular regions is determined according a suitable scale found after finding the extreme values of x and y coordinates in the signature region. The width of the annular regions varies from image to image because of the different sizes and orientations of the signature images. The number of annular regions for any signature image from the same or different authors is fixed. After the pixel data are extracted from the annular regions, these are normalized by dividing them with the total pixel data of the signature. The normalized data thus obtained represent the pixel density in the annular regions. This process of getting normalized data is repeated a number of times for the signatures of each author and thus average normalized data are obtained and saved. The same process of feature extraction is applied at the two stages of the signature recognition system; training stage as well as recognition stage. This signature recognition system was implemented by using Microsoft Visual C++ .NET frame work.

4. Experiment Setup

We test performance of our system for a dataset of 30 signature authors. Each author signed five signatures for system training which were scanned and saved as monochrome bitmap images. One of the bitmaps of signatures is shown in the Figure 1. The background of the bitmap is not free of noise.

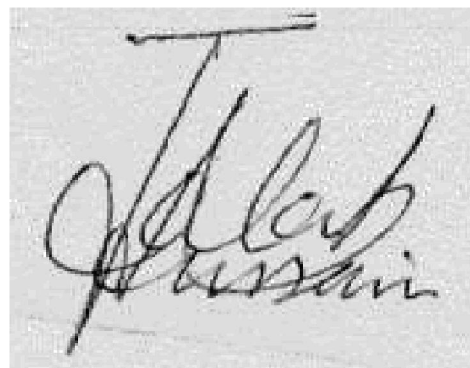

Figure 1: Scanned signature image with noise in the background

Noise is removed from the background of the bitmap to change it to white color as shown in Figure 2.

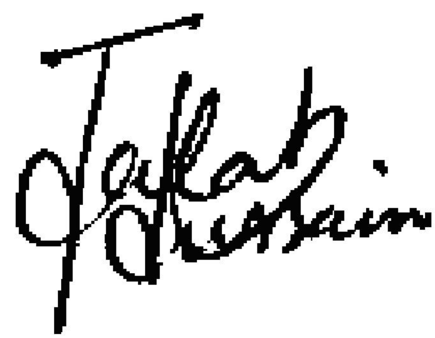

Figure 2: Signature outline extracted after noise removal

After finding the center the image was divided into 22 equal width annular regions. Pixels were counted in each annulus to compute normalized pixel densities for each annulus. Average values of the densities were stored for the number of signature samples used for system training. The same steps were repeated for each test signature sample at recognition time using minimum distance classifier.

5. Results and Discussion

Signatures from thirty authors were collected for training as well as recognition purposes. Each author was requested to provide five genuine signatures to train the system. The system was trained by using two, three, four and five genuine signatures of each writer. After training the signature recognition system, its performance was evaluated by observing the recognition of test signatures. Table 1 shows % false recognition rate (FRR) of the system while using two, three, four and five training signatures.

Table 1 show that error decreases as the number of training samples is increased. Other prominent attributes of this signature recognition system are elaborated as follows:

Table 1: Performance of signature recognition system

Training Samples	False Recognition Rate (%)
2	35
3	22
4	20
5	15

5.1. Rotation Invariance

A writer may sign at different angles at different times. The results obtained for signatures rotated at slightly different angles were found to be satisfactory. As the range of the orientation angles increases the results of signature recognition start becoming inconsistent. The sample signatures with different orientations used for training and testing are shown in Figure 3.

Figure 3: Rotation Variation in Signatures used in Training and Testing

5.2. Size Invariance

Our proposed feature extraction technique does not depend upon the sizes of the signatures used for training and testing and hence our signature recognition system does not degrade. The examples of bitmap samples of different sizes used for training and testing are shown in Figure 3.

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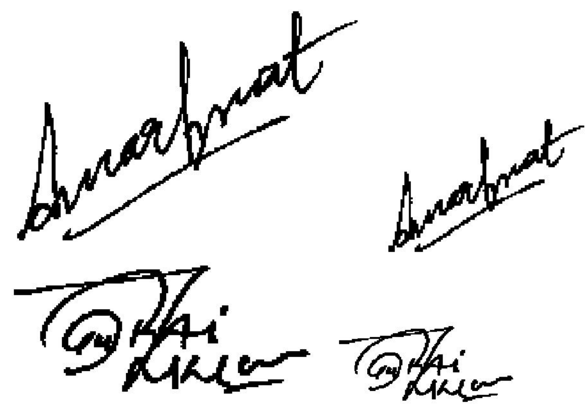

Figure 4: Size Variation in Signatures used in Training and Testing

5.3. Independent of writing pens

The results of our signature recognition system for signatures obtained from different writing pens are invariant of pen type used. We tested our system for signatures made through an ink pen or a ball point to be consistent.

6. Conclusions

A study of recognition of off-line static signature is presented in this paper. A technique of extracting discriminative feature set to impart a quality of the recognition system to tolerate variation in size and rotation of test sample of signature. The proposed technique used discriminative features of signatures based of geometric properties. The scanned signature images are first normalized by removing noise and centering the signature in the images in preprocessing step. Feature vectors are then extracted as normalized pixel density of 22 annular regions of equal width. We used 2 to 5 signature samples of thirty authors to train the system which was then evaluated with test signature samples for recognition rate. Test samples were made to vary in size and rotation. Our system tolerated appreciable variation in size and rotation of test signature samples. The false recognition rate of our system was 35%, 22%, 20% and 15% for training sample count to be 2, 3, 4 and 5, respectively.

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