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Offline Signature Verification

by

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Certificate

This is to certify that the work contained in this thesis entitled

Offline Signature Verification

is the work submitted by

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for the award of the degree of Bachelor of Technology, carried out in the Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati under my supervision and that it has not been submitted elsewhere for a degree.

Dr.Suresh Sundaram
(Project Supervisor)
Date: 19 Apr 2016

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Abstract

An off-line signature verification system based on contour features is presented.The total process was divided into two parts feature selection and matching strategies. For features we used Turning Angle Scale Space(TASS) along rows and columns, Equimass Segmentation (Grid approach), Contour-hinge PDF, Contour-direction PDF, Local Binary Pattern(LBP),Fusion of different features and for classifiers we used Dynamic Time Warping(DTW), Histogram Matching, Gaussian Mixture Model(GMM), Vector- Quantization(VQ). Performance of these methods were based on the equal error rate(EER). Verification was done on a sub-corpus of the MCYT signature database.Results were comparable to existing approaches based on different features. It is also observed that combination of the proposed features does not provide improvements in performance,maybe to some existing correlation among them.

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Chapter 1

Introduction

The increasing interest on biometrics is related to the number of important applications where a correct assessment of identity is a crucial point. In this thesis, we address the problem of automatic verification of writers on scanned images of signatures, known as off-line signature verification. This is a long-established pattern classification problem, since signature is one of the most widely used authentication methods due to its acceptance in government, legal, financial and commercial transactions.

There are two major methods of signature verification.On-line systems use special input devices such as tablets, while off-line approaches are much more difficult because the only available information is a static two-dimensional image obtained by scanning pre-written signatures on a paper; the dynamic information of the pen-tip (stylus) movement such as pen-tip coordinates, pressure, velocity etc. cannot be captured by an image scanner. The off-line method, therefore, needs to apply complex image processing techniques to segments and analyse signature shape for feature extraction.

Chapter 2

Preprocessing

2.1 Image preprocessing

As with most pattern recognition problems, preprocessing plays an important role in signature verification. Signature images may present variations in terms of pen thickness, scale, rotation, etc., even among authentic signatures of a person.

2.1.1 Noise Removal

Noise removal is required to eliminate the pixels that are not part of the signature, but contained in the image. When we scan signature from paper then some unwanted pixels comes with the scanned image that is not a part of the signature. We are median filtering on the binarized image of the original signatures.

2.1.2 Thinning

Thinning is a morphological process necessary for the reduction of data and computational time. To reduce all objects in an image to lines, without changing the essential structure of the image.

2.1.3 Region of Interest

In this step, region of interest i.e. the region where the signature is exactly situated is determined using auto cropping approach by calculating first foreground row, first foreground column, last foreground row and last foreground column. Region of Interest (ROI) is the signature object itself.

2.2 Database description

Verification is performed on a sub-corpus of the MCYT signature database which consisted of 75 users each having 15 genuine and 15 skilled forgery signature, out of which 5 genuine signature is taken as training and the rest as testing images.

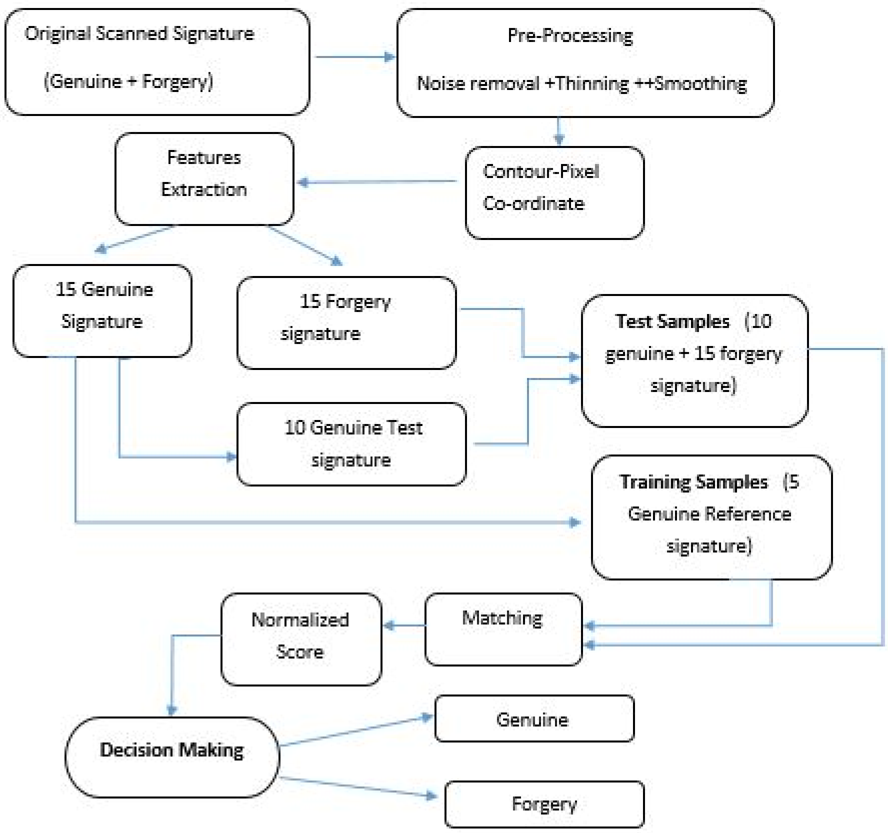

FIGURE 2.1: A schematic representation of the systems developed in this dissertation.

Chapter 3

Feature Extraction

We have used 4 main feature descriptors in our verification system.

1.Turning Angle

2.Equimass Segmentation

3.Contour Hinge and Direction pdf

4.Local Binary Pattern

3.1 Turning Angle

3.1.1 Turning Angle Sequence(TAS)

This concept of angle calculation is mainly proposed for online signature verification system but we are extending this for offline system. The Turning Angle (TA) in a signature is the angle between two consecutive segments connecting three points of the signature, while the TAS is the sequence of TAS along the signature. The TA at a point (x_k, y_k) is calculated by using the r$_{th} previous point($ x$_k - r, y_k - r)$ and the r$_{th} consecutive point($ x$_k + r, y_k + r)$ as shown below.

$$\theta_k^r = \arccos[\frac{(x_k - r, y_k - r), (x_k, y_k) \times (x_k, y_k), (x_k + r, y_k + r)}{|(x_k - r, y_k - r), (x_k, y_k)|.|(x_k, y_k), (x_k + r, y_k + r)|}]$$

In order to give an online flavour to our problem, we have focused on implementing the same concept to offline signature verification. Once the contour of the signature is extracted and the contour pixel co-ordinates were in our hand, we took all the contour pixels that are along one row of the signature image and calculated the turning angles at all these contour points individually (taking the r_{th} next point and r_{th} previous point from a particular contour point). Like this we calculated angles along all the rows and all the columns for one value of r.

3.1.2 Turning Angle Scale Space(TASS)

Combined use of TAS at different scales, that is, using different r values, produces the Turning Angle Scale Space (TASS) signature representation. More formally, for each contour point k of the signature, a number of angles are calculated for several values of r, providing simultaneous information at different observation scales.
Small r values correspond to finer description of local characteristics, while greater values capture coarser features of the signature. Computation of TAS involves proper setting

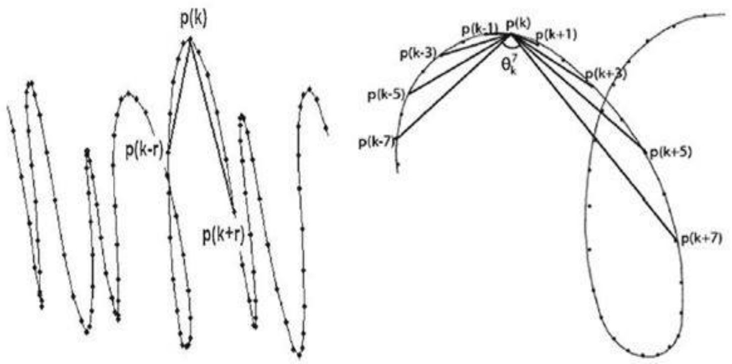

FIGURE 3.1: Turning angle for point P_k between segments $(P_k r, Pk)$ and $(P_k, P_k + r)$ for various r [3]

of parameter r. Parameter r defines the number of sample points of the angle sides and therefore defines the scale of curve observation. TAS for r = 1 is not a good choice as it suffers from noise between consecutive points. Small hand trembling may result in great TAS that gives the impression of turning directions while the segments may be parts of a straight line. Quantization effects contribute also to noise level uprising. For greater values of r this phenomenon is eliminated. By increasing r higher scale information is taken into account. However, angle is not computable in signature boundaries for r points, limiting the TAS length to N-2r points, where N is the number of signatures samples.

In between these two extreme cases, there is an extended range of r values that could be assigned to r and capture a great deal of signature information.

3.2 Equimass Segmentation

Signature regimentation is performed using an adaptive grid approach based on the Equimass approach, where the grid lines are found at the equimass divisions of the horizontal and vertical mass histogram of the signature image (the mass being defined as the number of black pixels). More precisely, let I(X,Y) be the signature image where:

$$I(x, y) = 0 \rightarrow whitepixel$$

$$I(x, y) = 1 \rightarrow blackpixel$$

If r horizontal (vertical) slices must be defined, the grid is designed so that the mass of each horizontal (vertical) slice is equal to $M_{region} = M/r$, being M the total mass of the signature image. Figures 3.2 shows the result of the segmentation algorithm for r=5 and r=10, respectively. Of course, when r=5, the number of regions is equal to 25; when r=10, the number of regions is equal to 100.

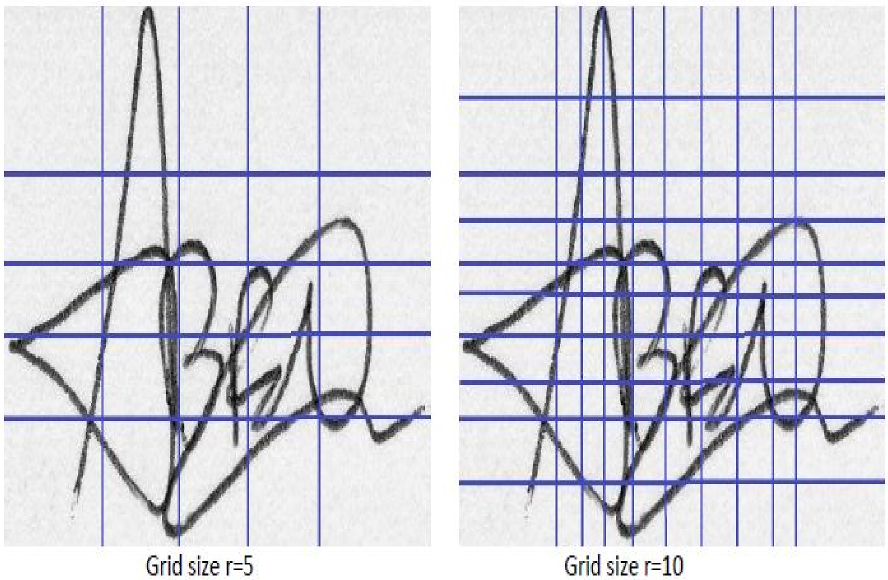

FIGURE 3.2: Signature Image Segmentation

3.3 Hinge Feature

3.3.1 Contour-Direction PDF (f1)

The contour-direction distribution f1 is extracted by considering the orientation of local contour fragments. A fragment is determined by two contour pixels (x_k, y_k) and (x_{k+r}, y_{k+r}) taken a certain distance r apart. The angle that the fragment makes with the horizontal is computed using

$$\phi = arctan(\frac{y_{k+r} - y_k}{x_{k+r} - x_r})$$

As the algorithm runs over the contour, the histogram of angles is built. This angle histogram is then normalized to a probability distribution f1 which gives the probability of finding in the signature image a contour fragment oriented with each ϕ. The angle ϕ resides in the first two quadrants because, without online information, we do not know which inclination the writer signed with. The histogram is spanned in the interval $0^o - 180^o$, and is divided in n = 12 sections (bins).

3.3.2 Contour-Hinge PDF (f2)

In order to capture the curvature of the contour, as well as its orientation, the "hinge" feature f2 is used. The main idea is to consider two contour fragments attached at a common end pixel and compute the joint probability distribution of the orientations ϕ_1 and ϕ_2 of the two sides. A joint density function is obtained, which quantifies the chance of finding two hinged contour fragments with angles ϕ_1 and ϕ_2 respectively. It is spanned in the four quadrants (360^o) and there are 2n sections for every side of the contour-hinge, but only non-redundant combinations are considered (i.e. $\phi_2 \geq \phi_1$).

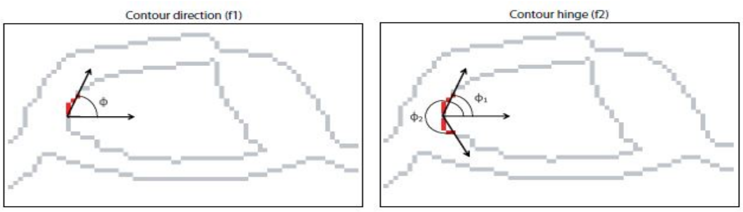

FIGURE 3.3: Graphical description of the feature extraction. From left to right: contour direction (f1), contour hinge (f2)

3.4 Local Binary Pattern

LBP is defined as a grayscale invariant texture measure and is a useful tool to model texture images.The original LBP operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the value of the central pixel and concatenating the results binomially to form a number. The thresholding function f(...)for the basic LBP can be formally represented as:

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

FIGURE 3.4: Example of 8-neighborhood around Z_o

$$f(I(Z_o), I(Z_i)) = 0 \quad if \quad I(Z_i) - I(Z_0) \leq threshold$$

$$f(I(Z_o), I(Z_i)) = 1 \quad if \quad I(Z_i) - I(Z_0) > threshold$$

$$i = 1, 2 \ldots 8$$

In our thesis a variant of lbp has been used.Around each contour point a mask (of size 7) has been taken consisting of only neighbouring contour points.The Turning Angle of the central pixel is compared with each of the right and left neighbouring contour points and assigned a bit value either 1 or 0. After obtaining the 6 bit binary number it is converted into its decimal equivalent(hence there were total 2^6 possible numbers).

In the fig 3.5 a bit value of [101010] and hence its decimal equivalent 42 is assigned to

X_{k-3}	X_{k-2}	X_{k-1}	X_k	X_{k+1}	X_{k+2}	X_{k+3}
30	120	10	45	60	40	150
1	0	1		0	1	0

FIGURE 3.5: Neighbouring Contour Angles and the bit values assigned

the central pixel.

Chapter 4

Matching Strategies

We have used 4 main classifiers for the task of verification.They are

1.Dynamic Time Warping(DTW)

2.Histogram Matching

3.Gaussian Mixture Model(GMM)

4.Vector Quantization(VQ)

4.1 Dynamic Time Warping(DTW)

There are inevitable variations in the signature patterns drawn by the same person. The present proposal is to track the positional variations of the features of the signature patterns and build a statistics of these variations from the training set. The one-dimensional projection profiles of the signature patterns are optimally matched using dynamic time warping. The positional variations are then derived from the resulting warping function:

$$D(i,j) = d(i,j) + min(D(i,j-1), D(i-1,j-1), D(i-1,j))$$

D is the accumulated cost matrix where D(i,j) is the cumulated distance. Now the warping path is constructed by finding the minimum distance point subjected to boundary conditions of continuity, and monotonicity. Total cost of matching is normalized with distance of the warping path to maintain the uniformity.

4.2 Histogram Matching

Each client of the system is trained by a set of 5 genuine signatures feature. For each feature, the histogram of the 5 signatures together is computed and then normalized to a probability distribution. To compute the similarity between a claimed identity q and a given signature i, the chi distance is used where p are entries in the PDF, n is the bin index, and N is the number of bins in the PDF (the dimensionality).

$$\chi^2_{qi} = \sum_{n=1}^{N} \frac{(p_q[n] - p_i[n])^2}{(p_q[n] + p_i[n])}$$

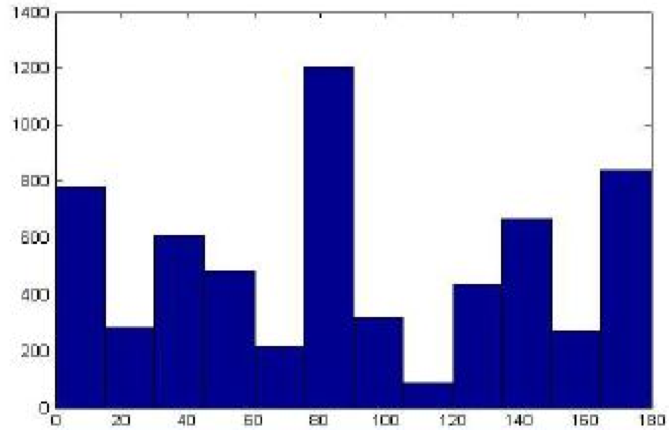

FIGURE 4.1: Histogram of 5 reference genuine signature of user1

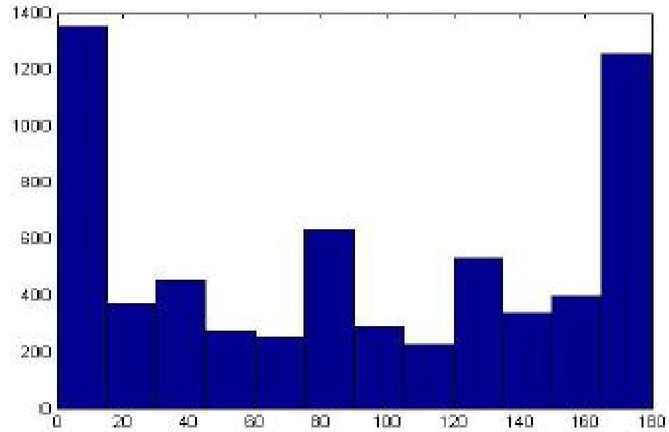

FIGURE 4.2: Histogram of a test signature of user1

4.3 Gaussian Mixture Model(GMM)

Gaussian Mixture Model (GMM) has been used for training our samples. For this we have taken 5 genuine signatures of each user and extracted the features from all of the samples after proper pre processing steps. The training phase uses Gaussian Mixture Model (GMM) technique to obtain a reference model for each signature sample of a particular user.
The formation of GMM is started by initialization of cluster centres such as means of Gaussian distributions chosen randomly and their shapes such as covariance matrices. The number of clusters or Gaussians to be used is provided by the users.
When the model gets trained, it is used to find the similarity rate between the query data (test set) and the model.By computing Euclidean distance between reference signature and all the training sets of signatures, acceptance range is defined. If the Euclidean distance of a query signature is within the acceptance range then it is detected as an authenticated signature else, a forged signature.

4.4 Vector Quantization(VQ)

Vector quantization is a classical quantization technique used in many applications such as image and voice compression, voice recognition. A vector quantizer maps k-dimensional vectors to a finite set of vectors Y = $\{y_i$: i = 1, 2, . . . , C$\}$. Each vector y_i is called a code vector or a code word and the set of all the code words is called a *codebook*. In our system, we concatenate all the reference signatures and codebook is generated. For every unknown signature, we encode the signature using each code word. For every point of unknown signature, we extract the code word with the minimum distortion and assign it to that point. The optimum number of code words (Codebook size) is a design parameter to be found out experimentally.

Chapter 5

Results

5.1 Turning Angle Sequence

5.1.1 DTW +TAS

At initial stage of our work we took average turning angles along every row and column as our feature vector (angles are found at every contour points for different radius).At later stage, angle for different r at every contour pixels were found and combined with the X and Y co-ordinate to form the feature vector.

The number of training samples for each user =5

The number of testing samples for each user=25

Feature Extraction Approach	MEER (in %)
1.TAS only along rows	26
2. TAS only along columns	27
3. TAS along rows and column both	18
4. X and Y co-ord along with TAS	25

Table 5.1: DTW +TAS

5.2 Equimass Segmentation

5.2.1 DTW + Equimass Segmentation

A local approach in which an Image was segmented into grids and an average of all the angles at each contour point of every grid is stacked to generate the feature vector.

The number of training samples for each user =5

The number of testing samples for each user=25

Grid Size	MEER (in %)
16 partitions of image (r=4)	20
49 partitions of image (r=7)	18

Table 5.2: DTW +Equimass Segmentation

5.3 Hinge Feature

5.3.1 Histogram Matching +Contour-Hinge pdf +Contour-Direction pdf

The number of training samples for each user =5

The number of testing samples for each user=25

Hinge Feature	MEER (in %)
Contour-Direction pdf (f1)	13.7
Contour-Hinge pdf(f2)	12.3
Contour-Direction pdf (f1)+ Contour-Hinge pdf(f2)	10.68

Table 5.3: Histogram Matching +Hinge Feature

5.4 Local Binary Pattern(LBP)

The number of training samples for each user =5

The number of testing samples for each user=25

Mask Size	MEER (in %)
4 Neighbour (4 bits)	25
6 Neighbour (6 bits)	22.1

Table 5.4: Histogram Matching +Hinge Feature

5.5 GMM +Contour-Direction pdf(f2)

The number of training samples for each user =5

The number of testing samples for each user=25

Cluster Size	MEER (in %)
64	28
128	24

Table 5.5: Histogram Matching +Hinge Feature

5.6 Fusing different Features

5.6.1 Histogram Matching + Hinge + LBP

We have fused hinge and Lbp feature using the weighted sum method and varying α.

$$score = (1 - \alpha) * d1 + \alpha * d2$$

The number of training samples for each user =5

The number of testing samples for each user=25

alpha	MEER (in %)
$\alpha = 0.7$	10.12
$\alpha = 0.5$	12.69
$\alpha = 0.3$	15.45

Table 5.6: Histogram Matching +Hinge Feature + LBP

Chapter 6

Conclusion

A machine expert for off-line signature verification based on contour features has been presented. Experimental results are given using 2250 different signature images of 75 contributors extracted from the MCYT signature database. The methods achieved satisfactory Mean Equal Error Rate(MEER) of 10.12%(Hinge +LBP), 10.69%(Hinge Features f1 +f2), 22%(GMM).
It is also remarkable that the combination of features does not result in performance improvement, maybe due to the correlation among them.Verification results are comparable to other existing approaches for off-line signature verification based on different features using the same experimental framework.This encourages us to exploit their complementary information using different fusion strategies. Another source of future work is to better analyze the information content in signature images in order to devise quality measures related to their utility for identity verification.

Chapter 7

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