IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

Offline Signature Recognition using Hough Transform and Neural Network

Rahul Dubey[*1] , Dheeraj Agrawal[2]
[*1]Department of Electronics and Communication, OIST Bhopal, India
[2] Department of Electronics and Communication, MANIT Bhopal, India
rahul.dubey0686@gmail.com

Abstract

Authentication of a person is the major concern in this era for security purposes. In biometric systems Signature is one of the behavioural features used for the authentication purpose. In this paper we work on the offline signature collected through different persons. Morphological operations are applied on these signature images with Hough transform to determine regular shape which assists in authentication process. The values extracted from this Hough space is used in the feed forward neural network which is trained using back-propagation algorithm. After the different training stages efficiency found above more than 95%. Application of this system will be in the security concerned fields, in the defence security, biometric authentication, as biometric computer protection or as method of the analysis of person's behaviour changes.

Keywords: Biometrics, Signature, Hough transform, Back propagation, Artificial Neural Network.

Introduction

Automatic person identification is the major challenges in this era of automation. How-ever, this is not a new problem for our society, and work in this field is a great task as per security concern. With the development of Internet, the interactions are becoming more and more automatic and thus the problem of identity of an individual has become more important. The traditional modes of person authentication systems such as Possessions and Knowledge are not able to solve this problem at the extent which required in today's era. Possessions include physical characteristics such as keys, passports, and smart cards. Knowledge is a piece of information that is memorized, such as a password and is supposed to be kept a secret. Due to inability of traditional techniques based authentication methods to handle the security concerns, biometrics research have gained significant momentum in the last decade as the security concerns are increasing in every field. Biometrics refers to authentication of a person using a physiological and behavioural trait of the individual that distinguish him from others. Handwriting is a behavioural biometric as it is generated as the consequence of an action performed by a person. Handwriting identification also has a long history[1]. The signature recognition is the process of writer's verifying by means of the samples signature that are comparing with stored in the database records. The result of this process is usually a number between 0 and 1, which represents a matching ratio. The signature recognition is one of many biometric identification techniques, which are used in practice. In the business world we sign things such as accounts and other official documents. Personal signature lends itself well for biometric verification in state–of–the–art electronic devices. Unfortunately, one drawback of signature is that people do not always sign documents in exactly the same manner. For example, the angle at which they sign may be different due to seating position or due to hand placement on the writing surface. In our approach, the signature analysis process is composed of three stages:

– pre–processing: where image binarization and its size standardization are performed,

– feature extraction: where the unique set of characteristics of the analysed signature is gathered using Hough transform,

– matching: extracted features trained in this step using Back propagation algorithm in Neural Network, then the personal signature is compared with the pattern from the signatures database.

Pre-Processing

A wide variety of devices capturing signature causes the need to normalize an input image of signature (so called: pre-processing). This stage is further sub-divided into following stages[2]:

 ISSN: 2277-9655
Impact Factor: 1.852

– Normalization, – Image Binarization, – Data Area Cropping, – Thinning.

A. .Normalization: Any further processing takes place, a noise reduction filter is applied to the binary scanned image. The goal is to eliminate single white pixels on black back ground and single black pixels on white background und .In order to accomplish this , we apply a 3 X 3 mask to the image with a simple decision, basic principle is this if the no of the 8 neighbours of a pixel that have the same color with the central pixel is less than two ,we reverse the color of the central pixel.Figure 1 and Figure 2 shows this stage

Fig.1 Original Image

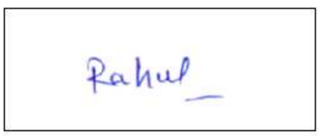

Fig 2. Normalized Image

B. Image Binarization: It allows us to reduce the amount of image information (removing colour and background), so the output image is black-white. The black-white type of the image is much more easily to further processing[2].

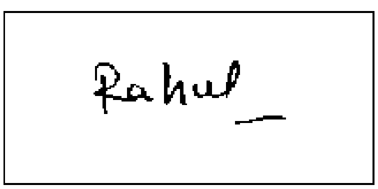

Fig 3. Binarized Image

C. Data Area Cropping: The signature area is separated from the background by using the well known segmentation methods of vertical and horizontal projection. Thus, the white space surrounding the signature is discarded[3]. Morphological operation Erosion and Dilation applied to perform this step.

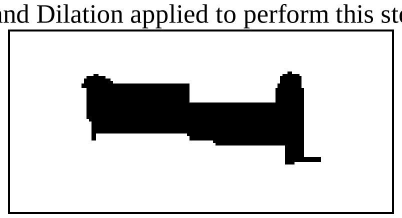

Fig 4. Erodated and Dilated Image

***D. Thinning[4]*:** Size of the image is reduced. In this procedure unnecessary signature areas are removed.
***Step 1*:** Mark all the points of the signature that are candidates for removing (black pixels that have at least one white 8-neighbor and at least two black 8-neighborspixels).
***Step 2*:** Examine one by one all of them, following the contour lines of the signature image, and remove these as their removal will not cause a break in the resulting pattern.
***Step 3*:** If at least one point was deleted go again to Step 1 and repeat the process once more. Fig.2. shows an example of this skeletonization technique. Skeletonization makes .

Fig 5. Edge detected image

Feature Extraction

During that step a gathering of characteristic data takes place. The output result is a set of the unique information about the signature. The choice of a powerful set of features is crucial in optical recognition systems. The features used must be suitable for the application and for the applied classifier .Global features provide information about specific cases concerning the structure of the signature, grid information and texture features are intended to provide overall signature appearance information in two different levels of detail. For grid information features, the image is segmented in 96 rectangular regions. Only the area (the number of signature points) in each region is utilized in order to form the grid information feature group. For the texture feature group to be formed, a coarser segmentation scheme is adopted. The signature image is segmented in only six rectangular areas, while, for each area, information about the transition of black and white pixels in the four deferent directions is used.
A. Image area: The number of black (foreground) pixels in the image. In skeletonized signature images, it represents a measure of the density of the signature traces.
***B. Vertical center of the signature*:** The vertical center Cy is given by

$$C_y = \frac{\sum_{y=1}^{y_{\max}} y \sum_{x=1}^{x_{\max}} b[x,\ y]}{\sum_{x=1}^{x_{\max}} \sum_{y=1}^{y_{\max}} b[x,\ y]}.$$

***C. Horizontal center of the signature*:** The horizontal center Cx is given by

$$C_x = \frac{\sum_{x=1}^{x\max} x \sum_{y=1}^{y\max} b[x,\ y]}{\sum_{x=1}^{x\max} \sum_{y=1}^{y\max} b[x,\ y]}.$$

***D. Maximum vertical projection*:** The vertical projection of the skeletonized signature image is calculated. The highest value of the projection histogram is taken as the maximum vertical projection.
***E. Maximum horizontal projection*:** As above, the horizontal projection histogram is calculated and the highest value of it is considered as the maximum horizontal projection.
***F. Vertical projection peaks*:** The number of the local maxima of the vertical projection histogram.
***G. Horizontal projection peaks*:** The number of the local maxima of the horizontal projection histogram.
***H. Number of edge points*:** An edge point is defined as a signature point that has only one 8-neighbor.
***I. Number of cross points:*.** Cross point is a signature point that has at least three 8-neighbors.
J. The Hough Transform: In the last stage the Hough Transform (HT) is used [5]. This algorithm searches a set of straightlines, which appears in the analyzed signature. The classical transformation identifies straight-lines in the signature image, but it has also been used to identifying of signature shapes. In the first step the HT is applied, where appropriate curve-lines are found. The analyzed signature consists of large number of straight-lines, which were found by the HT. The **Hough transform** is a feature extraction technique used in image analysis, computer vision, and digital image processing. Hough transform is the linear transform for detecting straight lines. For computational reasons, it is therefore better to parameterize the lines in the Hough transform with two other parameters, commonly referred to as *r* and θ (*theta*). Using this parameterization, the equation of the line can be written as

$$Y=x\cos(\theta)+y\sin(\theta)$$

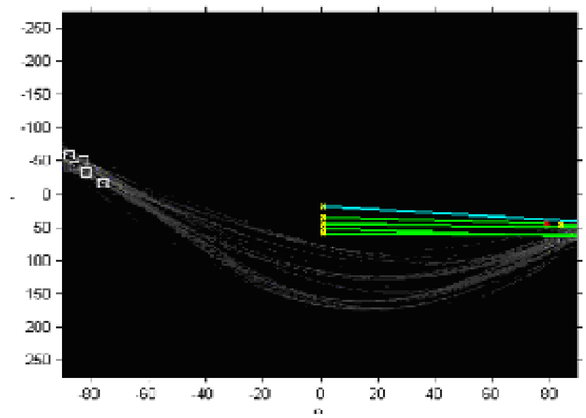

Fig 6. Hough transform image

Neural Network Training

Multi-layer Perceptron (MLP) neural networks are among the most commonly used classifiers for pattern recognition problems[6]. Despite their advantages, they suffer from some very serious limitations that make their use, for some problems, impossible. The first limitation is the size of the neural network. It is very dificult, for very large neural networks, to get trained. As the amount of the training data increases, this dificulty becomes a serious obstacle for the training process. The second dificulty is that the geometry, the size of the network, the training method used and the training parameters depend substantially on the amount of the training data. Also, in order to specify the structure and the size of the neural network, it is necessary to know a priori the number of the classes that the neural network will have to deal with. Unfortunately, when talking about a useful SRVS, a priori knowledge about the number of signatures and the number of the signature owners is not available. In this work a Backward Propagation neural network is used in order to have the final decision. The Backward Propagation neural networks are feed-forward architectures with a hidden non-linear layer and a linear output layer. The training of the system includes the following two steps. We have trained the network by randomly choosing the signature images from our available database .We passed the extracted features into the neural network and each time we changed the input weights to train the network. The extracted values of each signature images from the database of 150 images are given to the feed forward neural network (trained using back propagation gradient descent learning). Inferences are drawn by three cases:
Case 1. In this case data sets used for the training and testing are same.
Training Data set = 150 Images
Testing Data Set = 150 images

ISSN: 2277-9655
Impact Factor: 1.852

Case 2. In this case data set which is used for the training is greater than testing data set.
Training Data set = 150 Images
Testing Data Set = 120 images

Case 3. In this case data set which is used for the training is less than testing data set.
Training Data set = 100 Images
Testing Data Set = 120 images
In this model we use feed forward neural network with one single layer, two hidden layers and an one output layer. We use 35 neuron in the first hidden layer and 25 hidden layer in the second layer.

Signature Verification and Identification

It is done on the basis of FAR and FRR.
A. Rejection**:** The legitimate user is rejected because the system does not find the user's current biometric data similar enough to the master template stored in the database.
Correct rejection**:** The system was asked if the signature belonged to a false owner and the response was negative
False rejection: The system was asked if the signature belonged to the correct owner and the response was negative.

B. Acceptance**:** An imposer is accepted as a legitimate user because the system finds the imposter's biometric data similar enough to master template of a legitimate user.
Correct acceptation **:** The system was asked if the signature belonged to the correct owner and the response was positive.
False acceptation**:** The system was asked if the signature belonged to a false owner and the response was positive into groups and the adoption of a two-stage structure. We showed that such a structure leads to small, easily trained classifiers without hazarding performance by leaving out features that may be useful to the system.

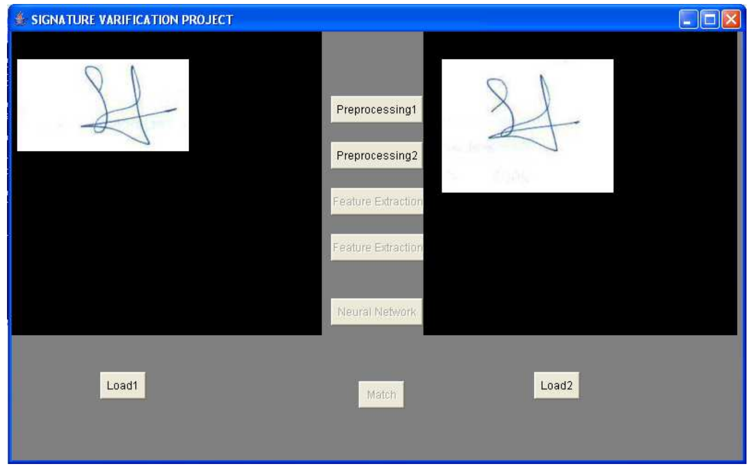

Fig 7 Signature selection

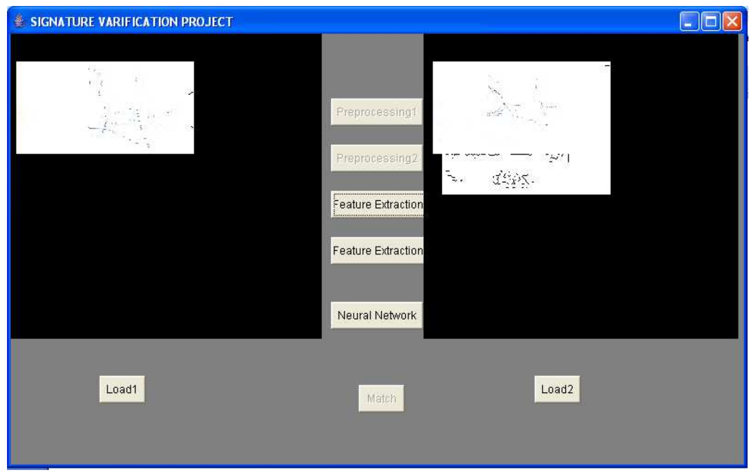

Fig 8. Preprocessed Image

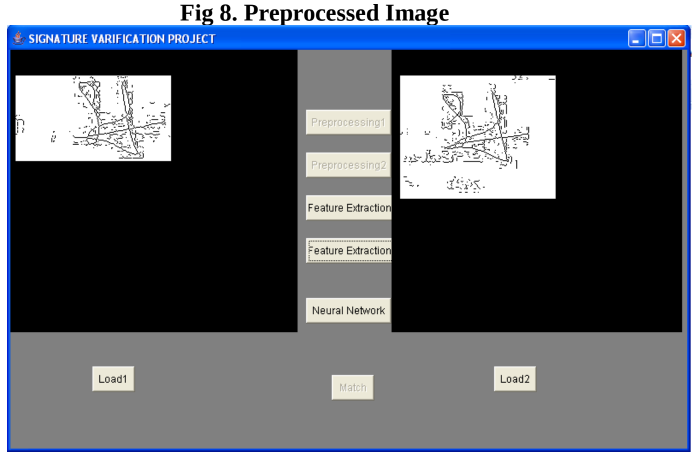

Fig 9 Feature extraction

ISSN: 2277-9655
Impact Factor: 1.852

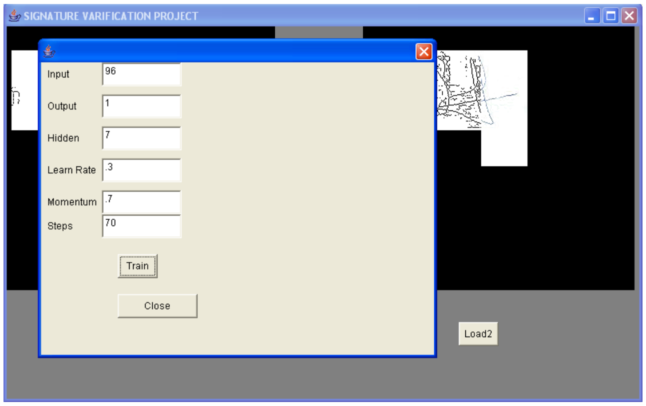

Fig 10 Neural Network training

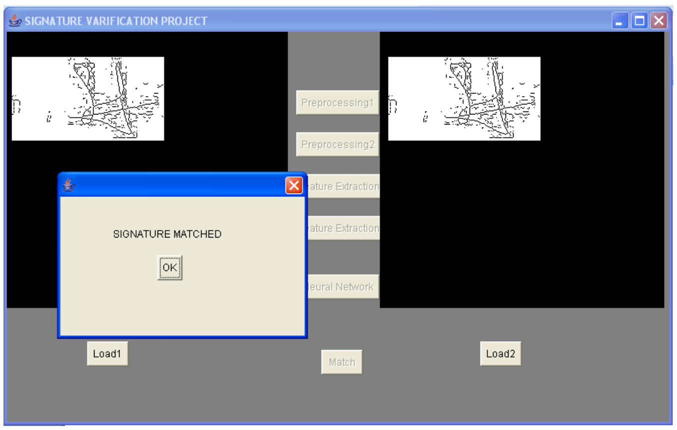

Fig 11 Verification result

Experimental Result

In the investigations, characteristic features (set of sections, projection, proportion coefficient, centre of gravity) have been tested separately, and the influence of the each feature has been observed. The test gave information about changes co-efficient FAR (False Accept Rate) and FRR (False Reject Rate). The FAR typically is stated as the ratio of the number of false acceptances divided by the number of total identification attempts. The FRR is stated as the ratio of the number of false rejections divided by the number of total identification attempt. Experimental results prove that the back propagation network performs well in identifying forgery. This proposed system might provide an efficient solution to unresolved and very difficult problem in the field of signature. A false rejection ratio of less than 0.1 and a false acceptance ratio of 0.17 were achieved in this system. In Different cases used parameters for neural nwteork are written in Table 1. Recognition and verification result are written in Table 2 and Table 3 respectively.

Parameter	Set 1	Set 2	Set 3
MOMEMTUM	0.9	0.85	0.78
LEARNING RATE	0.001	0.03	0.03
NO. OF HIDDEN LAYERS	2	2	2
EPOCHS	4800	4800	3500
NONLINEAR FUNCTION	*Logsig*	*Logsig*	*logsig*
Training Fuction	*T raingdm*	*Traingdm*	*traingdm*

Table 1. Parameters used for training in Neural Network

	Reference output	Sample output			FRR
		1	2	3	
Person 1	0.9	0.899	0.854	0.865	0.00
Person 2	0.9	0.882	0.867	0.875	0.00
Person 3	0.9	0.880	0.758	0.832	0.05
Person 4	0.9	0.890	0.895	0.645	0.045

Table 2. Recognition result for sample user

	Reference output	Sample output			FRR
		1	2	3	
Person 1	0.4	0.283	0.022	0.017	0.00
Person 2	0.4	0.210	0.204	0.108	0.00
Person 3	0.4	0.019	0.384	0.745	0.18
Person 4	0.4	0.008	0.547	0.578	0.16

Table 3. Verification result for sample user

Conclusion

A fundamental problem in the field of off-line signature verification is the lack of a pertinent shape factor. By using Hough Transform regular shapes determined which overcome problem of this pertinent shape. A major contribution of this work is the determination of a matrices point from Hough space transform which is used as an input parameter for the neural network which is further trained with back propagation algorithm. The experiments performed with a 150 signature database and efficiency in three different cases is found above 95% approximately.

In the future work application of the wavelet transform over Hough space image with application of

ISSN: 2277-9655
Impact Factor: 1.852

neural network will increase efficiency and reduce both false acceptance rate and false rejection rate. Further the fusion of handwriting parameters with signature can make system much better

References

[1] G. Sachin “Automatic Person Identification and Verification using Online Handwriting” , Thesis International Institute of Information Technology, Hyderabad, INDIA, March-2008.

[2] P.Porwik “The compact three stage method of the signature recognition”, proceeding on 6th International conference on computer Information system and Industrial Management applications, 2007.

[3] R.C.Gonzalez and R.E.Woods “Digital Image Processing”, second edition, ISBN81-7808-629-8.

[4] Pavlidis T.”A thinning algorithm for discrete binary images. Computer graphics and image processing 1980, 13:142-157.

[5] Illingworth J., Kittler J. A survey of the Hough transform. Computer Vision, Graphics and Image Processing 1988; 44: 87–114.
http://en.wikipedia.org/wiki/Artificial_neural_network, dated 14 march 2011