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# ONLINE SIGNATURE VERIFICATION USING NORMALIZED DYNAMIC FEATURE WITH ARTIFICIAL NEURAL NETWORK CLASSIFICATION

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## ABSTRACT
Handwritten signature verification system is most widely used in any financial and other documentation activities for authorization of identity of any human activity, but still these types of verification system are manly based on manual verification, that is a person only by looking compare the given signature with the test signature, so a more robust system is required which can be based on some computer based classification, so in this paper an online signature verification is proposed which is based on normalized dynamic features of the signature using artificial neural network as classification method, the proposed system used digital tablet with digital pen for acquisition of the signature and extract three dynamic features of the signature i.e., x,y coordinate of the signature along with the pressure at different points of the signature and from this dynamic features 11 different feature set is calculated and then using this feature set a neural network is trained for classification, the proposed system provide FAR of about 5% and FRR of about 6%.

**KEYWORDS**: Online signature, Dynamic features, Signature verification and Back-propagation neural network.

## INTRODUCTION
Signature, from the Latin word "Signare" meaning "Sign" is a stylized handwritten representation of a person's name or an identification mark that a person writes on documents/texts. Handwritten Signature is the most used biometric for any financial activities, authorization of documents etc, this types of biometric are called as behavioural biometric that is this biometric is related to the behavioural properties of the human being.

An automatic signature verification system can either be online or offline. In an offline verification system, the person sign on a paper using some pen and that signature are then converted into digital image using digital scanner and after pre-processing of signature image some characteristics properties of the signature image are extracted which are difficult to copy, then using some classification algorithms these features of the image is compared with the already stored features of the genuine image, if the comparison is above the pre-defined threshold then the signature is considered as genuine otherwise not. Other approach is online approach in which the user sign on digital tablet using digital pen and the dynamic data has been captured in real time and saved as database, then from this dynamic data like x,y coordinate, pressure, time etc., and from these data some features are calculated and that features are used to compared the different signature for forge detection. There are three types of forgeries related to signature verification system.

Random Forgery: In this type, the person who want to forge the sign only knows about the name of the person to whom which he want to forge the signature but does not know about the sign of that person.

Unskilled Forgery: In this type of forge, the person who want to copy the genuine signature are known about the way how a genuine signature was sign but does not able reproduce exactly.

Skilled Forgery: In this type the person who want to copy the sign knows very well about the way and different variation of genuine signature and the copy is very well match with the signature.

## RELATED WORKS

In 1996, **Luan L. Lee**, [1] presented an reliable on-line human signature verification systems, in which author uses a digital tablet for signature acquisition of more than 100 persons by taking total 10,000 signatures data in terms of x, y coordinates and time duration of signature. After that 42-different parameter feature set like Average writing speed, Maximum writing speed, Total signing duration etc. are calculated after that 49 normalized advanced features is extracted from it which and then majority classifier is used to find the genuine signature.

In 2015, **G. Pirlo**, [2] presented an multidomain verification of dynamic signatures using local stability analysis, in which Author uses SUSIG signature database which contain x, y coordinates, pressure values and time of acquisition of different coordinates Then, Split each signature into different predefined segments. Then, find the more stable domain of signature in each i.e., displacement, velocity, acceleration and pressure. Depending upon the best stable domain in a particular segment is recorded. Then in verification process, signature matching can be performed by using only the most stable domain of representation in each segment of the signature.

In 2011, **Zhan EnqiGuo**, [3] developed an online signature verification system for this author extract 15 static features and 32 wavelet coefficients from the signature, the static features like average speed in X and Y direction, ratio between minimum and maximum speed in X and Y direction etc., and then find the wavelet coefficients of the X and Y coordinates of signature and considered only high frequency coefficients.

In 2013, **VahabIranmanesh**, [4] author uses 20 genuine, 10 skill-forged, and 10 non skill-forged signatures, then author calculate the Pearson correlation coefficients between features of genuine signature and that correlation coefficients used as extracted feature for training feed-forward neural network with back-propagation learning.

## DATA ACQUISITION AND PRE-PROCESSING

It is the very critical task to perform, for this process it should be ensured that all the signature data should be accurate and within the limits. For this purpose in this paper a digital tablet of WACOM is used called WACOM bamboo with pressure sensitive pen as shown in Fig. 1, For data acquisition a this tablet is interfaced with computer with the help of C# code and a GUI has been developed in C# language as shown in Fig. 2,

***Fig1: System with digital tablet for signature acquisition***

User sign in real time on this tablet using pressure pen and that dynamic data like X, Y coordinates and pressure at different points are taken and saved in real time in text file. Ten signature per user are taken from 5 different users and stored their data in the form of X,Y coordinate and pressure form. The data collected is first normalized so that the features of high values will not dominate the features with low values.

***Fig2: GUI for taking signature data from tablet***

## FEATURES SELECTION AND EXTRACTION

The data is basically in the three parameter form i.e.,

I. X, Y-Coordinate of the signature at every point.
II. Pressure at different points of the signature.

So from this data many of the features can be extracted but for this paper only 11 different features are calculated. These are given below.

1) **Maximum value of the pressure ($P_{max}$):** It is the maximum value of the pressure that a person used to exert on tablet while signing the document.
2) **Minimum value of the pressure ($P_{min}$):** It is the minimum value of the pressure that a person used to exert on tablet while signing the document other then zero.
3) **Average value of the pressure ($P_{avg}$):** It is the average value of the pressure that a person used to exert on tablet while signing the document.
4) **Angle of Movement of first stroke($\theta_f$):** It is the direction of first movement of pen in x direction i.e., $\theta_{xf}=(Y_2-Y_1)/(X_2-X_1)$
5) **Average value of X-coordinates($X_{avg}$):** It is the average value of the X-coordinates used in signature acquisition

$$X_{avg} = \frac{1}{N}\sum_{k=1}^{N} X_k$$

6) **Average value of Y-coordinates($Y_{avg}$):** It is the average value of the Y-coordinates used in signature acquisition

$$Y_{avg} = \frac{1}{N}\sum_{k=1}^{N} Y_k$$

7) **Area of signature (A):** It is the total area on tablet acquired by signer during acquisition of the signature

$$A = [(X_{final} - X_{initial}) * (Y_{final} - Y_{initial})]$$

8) **Total change in x-direction ($T_x$):** It is the total change in X-direction.

$$T_x = (X_{final} - X_{intial})$$

9) **Total change in y-direction ($T_y$):** It is the total change in X-direction.

$$T_y = (Y_{final} - Y_{intial})$$

10) **First stroke length in X direction ($XL_{first}$):** It is the difference between X-coordinate at which the pressure is first zero after start of signature acquisition and initial value of X-coordinate.
11) **First stroke length in Y direction ($YL_{first}$):** It is the difference between Y-coordinate at which the pressure is first zero after start of signature acquisition and initial value of Y-coordinate.

Feature selection is very important in defining the accuracy of the system, some features provide better intra-signature variability then others.

## METHODOLOGY

There are two main phase of the signature verification system.

I. **Training Phase**

II. **Testing Phase**

Training Phase included the following steps

Take the Signatures of the persons on Wacom bamboo digital pad with pressure pen. Then extract the dynamic properties of the signature i.e., x, y coordinates of signatures and pressure on each pixels of the signatures at the time of signature is being made on tablet. Then extract the 11 different features of the signature from dynamic values of the signature as defined earlier. Then, make a database of the extracted features and train a neural network by back propagation technique using Levenberg-Marquardt (trainlm) training algorithm in MATLAB as shown in Fig.3.

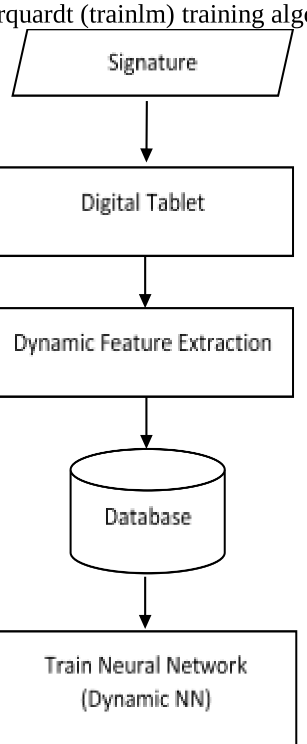


*Fig3: Training Phase*

**Testing Phase included the following steps:**

Take all type of forge signature (one at a time) i.e., Random forge, Unskilled forge and Skilled forge on digital tablet and extract the same dynamic features that uses in Training phase. Then, test the neural network that train in training phase using the extracted features as shown in Fig. 4.

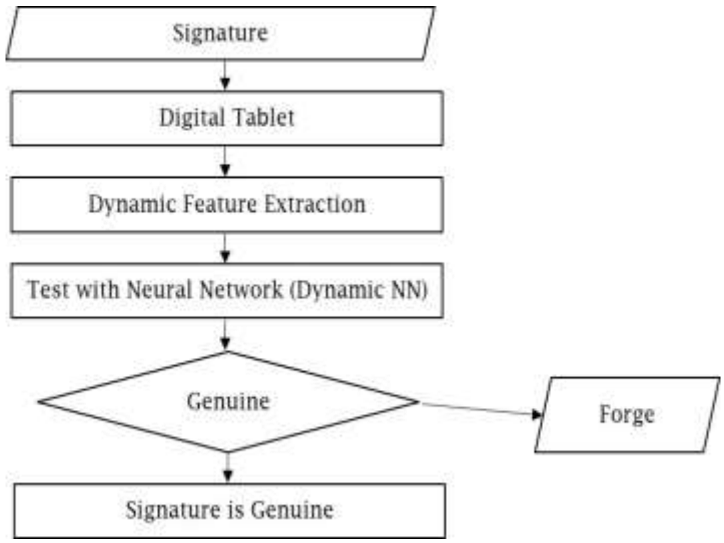


***Fig4: Testing Phase***

**Feed-forward Neural Network**: It is a fully connected network with three layers as shown in Fig. 5, Each layer contain one or more neurons to receive the input signal and process it by adding each signal after that applying threshold to produces the output. This types of network has the capability to learn by adjusting its weights which connecting one neuron in one layer to other neuron in other layer comparing the result output this is called supervise learning that is output is present and system compare the calculated result with the expected result and depending upon the difference in expected and calculated output the weight of the connection changes.

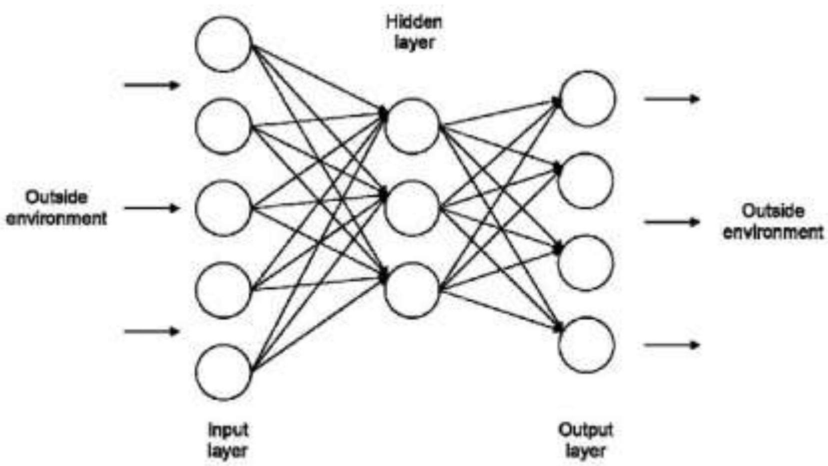


***Fig. 5 Feed-forward Artificial Neural Network***

## RESULTS AND DISCUSSION

This section reports the results of the testing conducted on artificial neural network using features data extracted from the online signature. To find the accuracy of the system the system has been tested for two types of error that is False

Acceptance Rate (FAR) it is the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user and other is False Acceptance Rate (False Rejection Rate) is the probability that the system incorrectly rejects access to an authorized person, due to failing to match the biometric input with a stored template. For this system the number of hidden layer is chosen is 20 and sigmoid activation function is used for hidden layer

For this research 10 signature of 5 different persons are taken to train the network and test the system for forge detection.

***Table 1: Performance Analysis of Proposed System with Existing System***

| System | FAR | FRR |
|---|---|---|
| Proposed System | 5 % | 6 %. |
| [1] | 1% | 20% |
| [5] | 9% | 19% |
| [3] | 1% | 6% |

## CONCLUSION

Handwritten Signature is mostly used in all financial transactions for authorization of identity of human but still these authentication system is based on by comparing the signature with authorized signature manually. So a system is required which is based on computer based classification. In this paper an online signature verification system is proposed which is based on artificial neural network based classification. This system 10 signatures of 5 different persons are taken on digital tablet using digital pen and from that a database of x, y coordinate and pressure values at different points are extracted, from which 11 different specific feature set is calculated, which is used to train a neural network using MATLAB software, the proposed system provide the better result in terms of FAR which is 5% and FRR which is 6% in comparison to already developed systems.

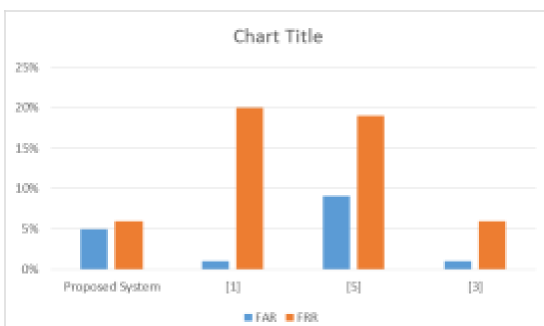


***Fig 6: Comparison Chart***

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