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Online Signature Verification with Periodic Template Updating Mechanism

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***Abstract*— Signature is most common method of authentication of a person. It is accepted worldwide. There are many application where signatures are being used as the primary means of authentication, such as banking and biometric attendance system. But signatures are much less accurate than other biometric authentication methods such as iris and finger prints. The main reason behind this inaccuracy is that the signature of a person may change with time and hence making it prone to forgery. This variation in signature is known as intra person variability. In this paper a method is proposed which can make the signature verification method independent to intra person variability. The proposed system updates the template signature's parameters. The efficiency increases by 5% as compared to the existing systems. SUSIG database is used for the implementation of the proposed algorithm.**

***Index Terms*— FAR, FRR, Neural Network**

I. Introduction

There are many biometric authentication methods such as authentication using an iris or finger prints. All these techniques require the identifying information of a user. This information is basically unique for an individual and it is widely accepted that no two users have the same information. These characteristics are regarded as physical characteristics. But there are some behavior characteristics such as voice and signature of a person. These behavior characteristics can be used in an authentication system [1]. It's been very long that signatures are considered a typical and reliable form of authentication system in our society. Signatures are very convenient way to represent the identity of an individual. This is the reason that signature authentication method is gaining the attention of researchers.

The signature of a person may be simple or complex in its appearance but it is a unique variation due to the unique variation in the geometry of human hand. The signature of a person is the reflection of his or her expression and identity. Signature tells a lot about the nature of a person. Signatures are not sudden creation of a person. The signatures evolves gradually and may be affected by the psychological, physical and emotional condition of that person. The signature of a person may change significantly over a short period of time or it may remain almost same over a long period of time.

The foremost desirable property of a signature verification system is that, it must be capable to detect forgeries. In forgery detection the verification system must detect the forged signatures but at the same time the genuine signatures should be identified. Signature verification method is mainly divided in two categories: Offline signature verification and online signature verification. These two methods are categorized on the basis of technique through which signatures are captured. In offline signature verification, the user signs on a piece of paper, these signatures are scanned by a scanner or a picture may be taken from a digital camera, the features are extracted and the signature is analyzed. Online signature verification method requires a pen tablet set to capture the signature. The online signature contains a far more information than an offline signature. Online signature verification method is much more efficient than offline signature verification method. The Offline and Online methods of signing are shown in figure 1 and figure 2 respectively.

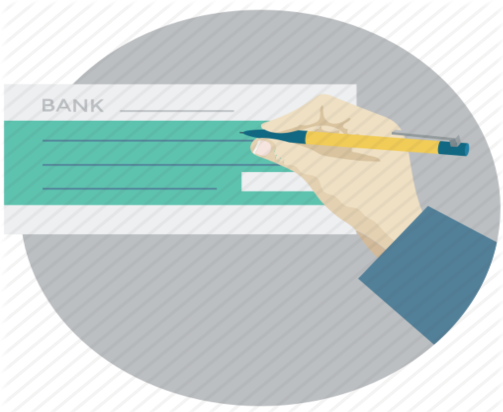

Fig. 1: Offline Method of signature

Fig. 2: Online Method of signature

II. Parameters Affecting the Signatures

Two main challenges in signature verification are: Inter-person variability and Intra-person variability.

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Inter-person variability is observed when a skilled forger forges, with high resemblance, the signature and perform forgery. Intra-person variability is observed when there are significant differences in the signatures of the user taken at different times. Hence, a signature verification system must be insensitive to intra-personal variability, but sensitive to interpersonal variability [3].

Generally the signatures are signed very fast because they have been practiced for the life time of the user. But, the speed of the signing process may change over a long time and hence generating a completely different signing speed. Since the online signature verification method uses a digital pen-tablet so unfamiliar signing surface may also affect the signature.

A signature verification method must be able to recognizing signatures while ignoring the variations such as: change in signatures due to different pens and it should also take into account that two signatures of a same person are mostly different.

A signature verification system must detect the forgeries with high rate and the rate of rejection of genuine signatures must be reduced.

III. Feature Extraction and Implementation Algorithm

In this paper following features of signatures are considered:

the curvature differences between two consecutive points, the x and y coordinate differences between two consecutive points, x–y coordinates relative to the first point of signature trajectory, pressure information as an additional local feature, center of gravity, ratio of length to width, the ratio of height to width, write time ratio, total time, signature duration, the maximum relative time value, maximum value of pressure and average value of pressure.

The proposed method differs from the previous work in the way that this method updates these parameters. The overall process can be explained as follows.

A set of reference signature is taken to extract the features of signatures. These features properly characterize the signature of an individual. These features are used to train neural network. This phase is known as enrollment phase.

To check a test signature, same features are extracted from the test signatures and these features are used to validate the test signatures. This phase is known as testing phase.

Two parameters, FAR (False Acceptance Rate) and FRR (False Rejection Rate), are used to describe the performance of the system. These two parameters are described as

FAR=(Number of falsly accepted signatures)/(Number of tested signatures) (1)

FRR=(Number of falsly rejected signatures)/(Number of tested signatures) (2)

The feature's coefficients were periodically updated with binary exponential update method. This method can be described as follows

Let x(n) be the value of coefficient at time n, and y(n) is the final coeffiocint value then

$$y(1)=x(1) \quad (3)$$

$$y(2)=0.5y(1)+0.5x(2) \quad (4)$$

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$$y(n)=0.5y(n-1)+0.5x(n) \quad (5)$$

In this way the coefficient value does not only contain the initial value but it also contain the present value of the coefficient.

These coefficients are extracted from online signatures. Some of the signatures that were used for this algorithm, and were taken digitally, are shown from figure 3 to figure 6.

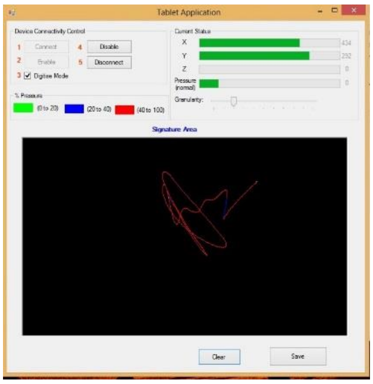

Fig. 3: First sample signature, taken from digital pen-tablet

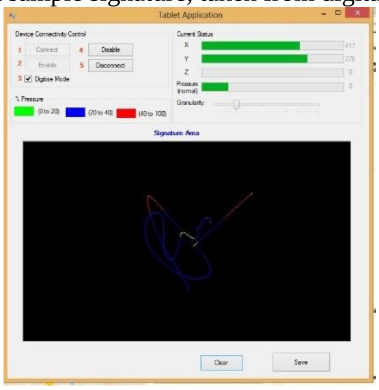

Fig. 4: Second sample signature, taken from digital pen-tablet

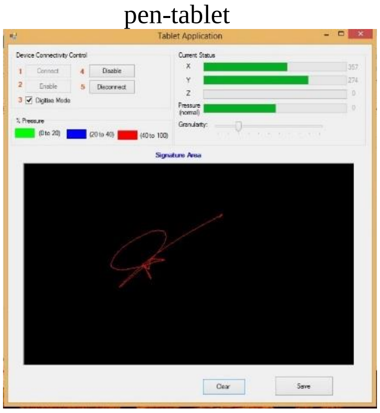

Fig. 5: Third sample signature, taken from digital pen-tablet

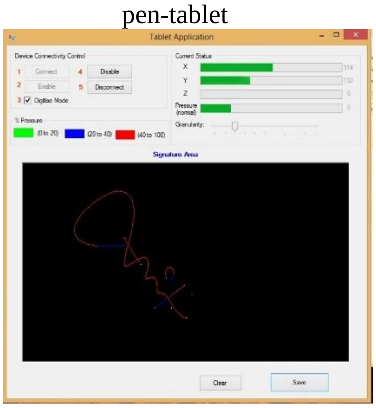

Fig. 6: Fourth sample signature, taken from digital pen-tablet

IV. Results and Discussion

The features were taken from these signatures and were updated at the time interval of 15 days. Some (out of 30) features are taken as an example to explain the complete algorithm.

The initial values of some coefficients are shown in Table 1.

Table 1: Initial values of some coefficients

User	Mean Pressure	Pen Up	Height to Width Ratio	Total duration
User 1	240.2133	3	0.546154	2520
User 2	500.0217	0	3.623457	910
User 3	681.5517	5	2.98481	2240
User 4	655.0498	3	2.889381	3333

The values of some coefficients after first time interval (15 days) are shown in Table 2.

Table 2: The values of coefficients after first time interval (15 days)

User	Mean Pressure	Pen Up	Height to Width Ratio	Total duration
User 1	345.0959	0	0.765866	2180
User 2	553.7481	0	3.695341	1340
User 3	662.0745	4	3.016548	2260
User 4	647.7689	3	2.573276	2858

The coefficients in table 2 were updated in accordance with the equation 3 to equation 5. Thus updated coefficients were used to train the neural network. These coefficients are shown in table 3.

Table 3: The values of updated coefficients after first time interval (15 days)

User	Mean Pressure	Pen Up	Height to Width Ratio	Total duration
User 1	292.6546	1.5	0.65601	2350
User 2	526.8849	0	3.659399	1125
User 3	671.8131	4.5	3.000679	2250
User 4	651.4094	3	2.731328	3095.5

The values of some coefficients after second time interval (30 days) are shown in Table 4.

Table 4: The values of coefficients after second time interval (30 days)

User	Mean Pressure	Pen Up	Height to Width Ratio	Total duration
User 1	394.0553	1	0.769164	2620
User 2	610.404	0	3.955056	980
User 3	672.0455	5	3.148276	2290
User 4	584.873	3	3.676712	2986

The coefficients in table 4 were updated in accordance with the equation 3 to equation 5. Thus updated coefficients were used to train the neural network. These coefficients are shown in table 5.

Table 5: The values of updated coefficients after second time interval (30 days)

User	Mean Pressure	Pen Up	Height to Width Ratio	Total duration
User 1	343.355	1.25	0.712587	2485
User 2	568.6445	0	3.807227	1052.5
User 3	671.9293	4.75	3.074478	2270
User 4	618.1412	3	3.20402	3040.75

The resultant system was then tested. The FAR and FRR shows an improvement using this method.

V. Conclusion

In this paper a novel method for signature verification is presented. The feature's coefficient values that are used to train the neural network are periodically (after 15 days in this case) updated. In this way the coefficient value contain the most recent changes that may appear due to physical or emotional state of the person while keeping the basic information intact. Since the coefficients are updated regularly so the FRR decrease continuously. Without updating the coefficient the FRR was 9.5%. After implementation of this algorithm the FRR improves to 4.4%. Same is the case with FAR, which improves from 11.2% to 6.2%. In this way the performance of the system may maintained constant over a long period of time, which was not possible with earlier methods.

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