A New Approach to Predicting Physical Biometrics from Behavioural Biometrics

Raid R. O. Al-Nima, S. S. Dlay, W. L. Woo

Abstract—A relationship between face and signature biometrics is established in this paper. A new approach is developed to predict faces from signatures by using artificial intelligence. A multilayer perceptron (MLP) neural network is used to generate face details from features extracted from signatures, here face is the physical biometric and signatures is the behavioural biometric. The new method establishes a relationship between the two biometrics and regenerates a visible face image from the signature features. Furthermore, the performance efficiencies of our new technique are demonstrated in terms of minimum error rates compared to published work.

Keywords—Behavioural biometric, Face biometric, Neural network, Physical biometric, Signature biometric.

I. INTRODUCTION

BIOMETRIC recognitions is used to identify people by their voices, faces or even gaits. One application of this is in legal and law where it is used to increase the accuracy of criminal identifications. Moreover, biometrics are increasingly used to verify the personal recognition and authentication [1].

In general, biometrics are divided into main different types: physical or behavioural characteristics [2]-[4]. The first type depends on the personal physiology, such as, hand geometry or fingerprint. The second type considers the personal behaviours or manners. For instance, the cursive writing and voice. Physical biometrics are usually more accurate and reliable, whereas the behavioural biometrics may affect by the illness or stress [2] shown in Fig. 1.

Many published papers have concentrated on single specific biometrics for identification such as iris [5], fingerprint [6], retinal [7], signature [8], DNA [9], speech [10] and face [11]-[17].

Several researchers have focused their attention on generating one biometric type from another. Examples of these are, eye generations from fingerprints which is presented by Sağiroğlu and Özkaya using an artificial neural network [18]. Similarly, facial features from fingerprints are generated based on an artificial intelligent technique [19]. Stationary face parts from the fingerprints are automatically produced in [20] based. Özkaya and Sağiroğlu also proposed an intelligent and automatic system which is designed and developed to investigate the relationship between fingerprints and faces [21].

Therefore, predicting physical biometric from behavioural biometric is challenging. The aim of this paper is to implement a new system for predicting faces from signatures by using the multilayer perceptron neural network (MLP) method. Furthermore, comparisons with other research shows the improved performance of the novel approach.
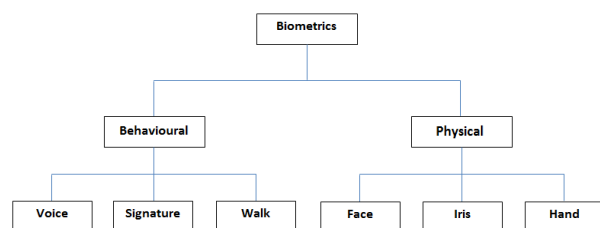

Fig. 1 Biometric types

II. HANDWRITTEN SIGNATURES

Signature is one of the oldest biometric types used for marking documents or identifying persons. Signature identification is considered a difficult task, because it is hard to get two identical signatures. There are many ways for people to write, such as the direction of writing, illumination, use of pen and many other parameters. Moreover, the signature systems cannot recognize a signature, because many people do not write in the same manner on each occasion, their samples tend to vary markedly [22]. Fig. 2 shows sample of signatures.
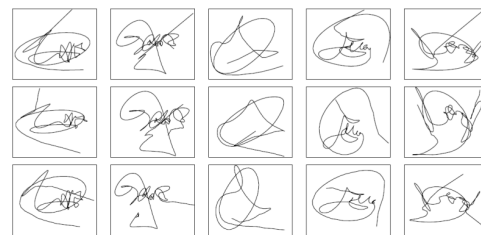

Fig. 2 Sample of signatures [23]

The signature databases in this research is the benchmark data Biometric Ideal Test (BIT) [24]. This benchmark data is being used as it allows our results to be compared with [23], [25] and [26] as they use the same database. The general algorithm of the signature database acquisition comprises three stages as shown in Fig. 3. Firstly, applying the Discrete Foriour Transform (DFT) for the signature to generate x and y

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in frequency domains. Secondly, pressure function is produced as a trajectory signal. Finally, all signals are presented in the time domain [25].
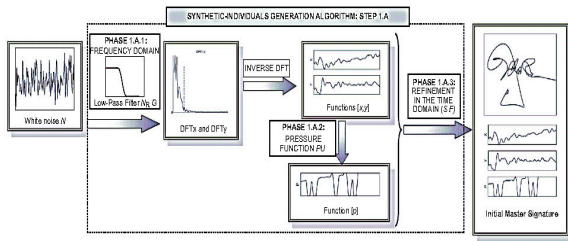

Fig. 3 General algorithm of the signature data acquisition [25]

It is worth mentioning that the pressure function has two characteristics: Number of penups and pendown. The first factor is a binary number where '0' represents the hand lifting from the paper and for '1' pendown. The second factor is the pressure on the paper. To get more accurate data from the signature in the time domain, several improvements are applied such as smoothing, flourishing, scaling, rotating and translating transformations [25].

III. FACE RECOGNITION

Face recognition is regularly used for identification, because of its accuracy and dependability [18]. The total differences between faces is caused by genes where the main features of the faces are settled. Several similarities could be found between the unrelated individuals. Whilst, children and parents have general similarity, because of their genes. Brothers and sisters have more similarities, especially between the twins. Thus, it is easy to recognize the faces of different people, but identifying identical twins is complex and very difficult for the biometric recognition system [19].

Automatic face recognition is a challenging issue. Many techniques have been implemented and refined for face recognition [27]. One promising method is to use artificial intelligent technique to establish the face automatically and facilitates face recognition for various work places, such as police and security purposes [18]. Moreover, predicting a face image from another biometric is not an easy task [21].

Fig. 4 shows type of faces which are used in this research.
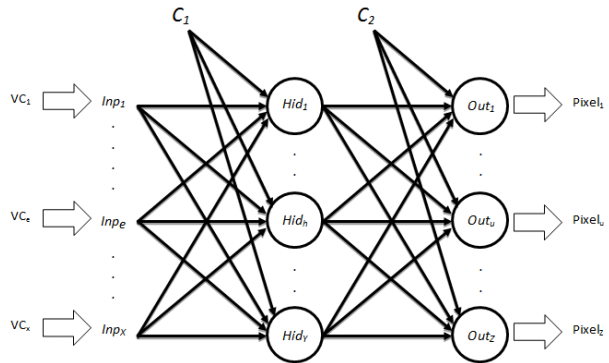

Fig. 4 Type of faces which are used in this research

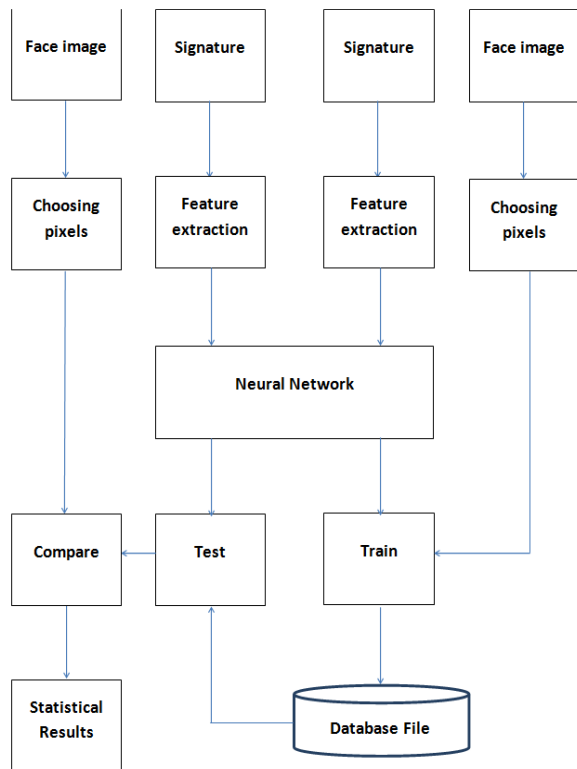
Fig. 5 The proposed MLP neural network

Fig. 6 The block diagram of the proposed method

IV. PROPOSED METHOD

In this paper, we propose a methodology to predict faces images from signatures based on a MLP neural network, where each person has his own network. In this method, 350 samples have been used; 6 samples for each person for training and 4 samples for testing. The inputs are the coefficient of variance of the signature after widowing / segmenting its database into 2D matrices with 5×4, 7×4, 9×4 and 11×4 elements. The lengths of signatures vary, so, zero padding is employed to equalize the size of the MLP inputs.

There are two training types of neural networks: supervised and unsupervised. Simply, the first type needs targets in the training part, whereas the second type does not [28]. The proposed supervised neural network uses face as a target after

choosing the pixels, which covers 40% of the original face image. Finally, after the testing stage the outputs are rearranged to be displayed as a two dimensional face image.

The activation function used in the hidden layer is the logarithm sigmoid. This is appropriate because there are no negative values and the output layer is a pure linear activation function. The architecture of the MLP network is given in Fig. 5. The block diagram of the proposed method is described in Fig. 6.

The Mean, Standard Deviation and Coefficient of Variance are shown respectively in (1), (2) and (3) [29]:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (1)$$

$$S_{td} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (2)$$

$$CV(\%) = \frac{S_{td}}{\bar{x}} \times 100\% \qquad (3)$$

In the last equation, the percentage is removed to avoid the overload in the MLP neural network.

The feedforward equations to calculate the outputs from the inputs are illustrated in (4) and (5) below:

$$Hid_h = f(C1_h + \sum Inp_e \times S_{eh}) \qquad (4)$$

$$Out_u = f(C2_u + \sum Hid_h \times Q_{hu}) \qquad (5)$$

where *Inp* is the input neurons in the input layer, *Hid* is the hidden neurons in the hidden layer, *Out* is the output neurons and it represents the output of the MLP. *C1* is the bias in the hidden layer, *C2* is the bias in the output layer, *e* is the counter of the input neurons (*e=1,2, …, X*), *h* is the counter of the hidden neurons (*h=1,2, …, Y*), *u* is the counter of the output neurons (*u=1,2, …, Z*). *S* is the connection weights between the input and the hidden layer and *Q* is the connection weights between the hidden and the output layer.

As mentioned earlier, the activation function in the hidden layer is the logarithm sigmoid shown in (6) [30]:

$$f(C1_h + \sum Inp_e \times S_{eh}) = \frac{1}{1 + e^{-(C1_h + \sum Inp_e \times S_{eh})}} \qquad (6)$$

Again, the activation function in the output layer is linear, which means that the neuron's output signal will be the same as the neuron's input signal. As shown in (7):

$$f(C2_u + \sum Hid_h \times Q_{hu}) = C2_u + \sum Hid_h \times Q_{hu} \qquad (7)$$

Then, the error is calculated between the output and the target by using (8) below:

$$\varphi_{out} = \frac{1}{Z} \times \sum(tar_u - f(C2_u + \sum Hid_h \times Q_{hu}))^2 \times \acute{f}(C2_u + \sum Hid_h \times Q_{hu}) \qquad (8)$$

Hence, the function of the output is linear and the derivation

of the linear is equal to 1. This will summarize (8) to (9) below:

$$\varphi_{out_u} = \frac{1}{Z} \times \sum(tar_u - (C2_u + \sum Hid_h \times Q_{hu}))^2 \qquad (9)$$

After that, the error in the hidden layer is calculated. See (10):

$$\varphi_{hid_h} = (\sum \varphi_{out_u} \times Q_{hu}) \times \acute{f}(C1_h + \sum Inp_e \times S_{eh}) \qquad (10)$$

The derivative function in the hidden layer is shown in (11) [28]:

$$\acute{f}(C1_h + \sum Inp_e \times S_{eh}) = \\ f(C1_h + \sum Inp_e \times S_{eh})[1 - f(C1_h + \sum Inp_e \times S_{eh})] \qquad (11)$$

That is:

$$\acute{f}(C1_h + \sum Inp_e \times S_{eh}) = \\ \frac{1}{1 + e^{-(C1_h + \sum Inp_e \times S_{eh})}} \times \left[1 - \frac{1}{1 + e^{-(C1_h + \sum Inp_e \times S_{eh})}}\right] \qquad (12)$$

Thus, (10) could be recalculated as in (13):

$$\varphi_{hid_h} = (\sum \varphi_{out_u} \times Q_{hu}) \times f(C1_h + \sum Inp_e \times S_{eh}) \\ \times [1 - f(C1_h + \sum Inp_e \times S_{eh})] \qquad (13)$$

or

$$\varphi_{hid_h} = (\sum \varphi_{out_u} \times Q_{hu}) \times \frac{1}{1 + e^{-(C1_h + \sum Inp_e * S_{eh})}} \\ \times \left[1 - \frac{1}{1 + e^{-(C1_h + \sum Inp_e * S_{eh})}}\right] \qquad (14)$$

The output error is computed to specify the weight values for the connection links between the hidden and the output layers. Similarly, the hidden error is calculated to determine the weight adjustment values for the connection links between the input and the hidden. All new weight values are computed according to the scaled conjugate gradient algorithm in [31].

V. RESULTS AND DISCUSSIONS

A training curve for a proposed MLP is given in Fig. 7. It is clear that the training curve is declines towards the goal and achieves the minimum Mean Square Error (MSE) value.

The Regression (R) is used to evaluate the MLP in the training stage. The regression is implemented to calculate the outputs of the network with respect to the desired output (or the target) in the case of testing, validating and training sets. The best fit means that the data is distributed along the 45 degree line, where the target is equal to the output [30]. The *R* value in this paper is equal to 1 which indicates a best fit between the target and the output, see Fig. 8.

To evaluate our work, general and statistical comparisons with other published work [18]-[21]. Table I illustrates the general comparisons.
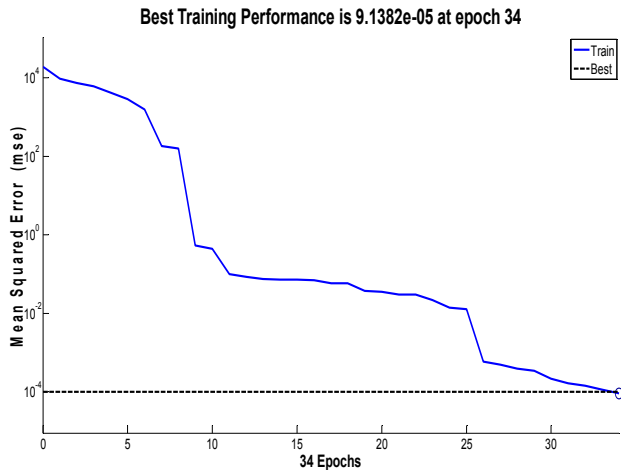
Best Training Performance is 9.1382e-05 at epoch 34

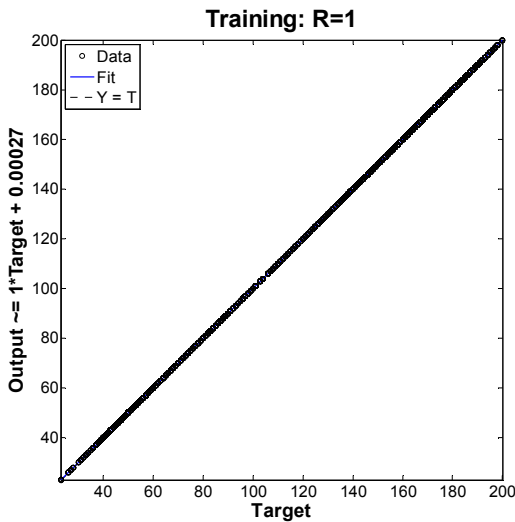Fig. 7 The training curve of an MLP neural network

Training: R=1

Fig. 8 The regression of a MLP neural network

TABLE I
GENERAL COMPARISON BETWEEN THIS WORK AND OTHER PUBLISHED PAPERS

Methods	Predicting	Number of samples	Transfer functions
Proposed Method	Face details from signature	350 samples (210 for train and 140 for test)	'logsig' in the hidden 'purelin' in the output
Sağiroğlu and Özkaya [18]	Eye generation from fingerprint	120 samples (80 for train and 40 for test)	---
Sağiroğlu and Özkaya [19]	General face features from fingerprint	"10-fold cross trained and tested 10 times with 10 different data sets"	Sigmoid function (SF) for the optimum design
Sağiroğlu and Özkaya [20]	Stationary face parts from fingerprints	120 samples (80 for train and 40 for test)	---
Özkaya and Sağiroğlu [21]	Total face features from fingerprint	120 samples (90% for train and 10% for test)	Having the parameters according to Taguchi technique

According to these general comparisons, our proposed approach predicted face details, whilst in the other published papers only some faces parts are generated. In addition, the number of training and testing samples in this work are much more than the number of samples in the other works.

Other comparisons are applied by using the statistical errors based authentication where they have been used by researchers. These statistical errors are: Sum Squared Error (SSE), Mean Squared Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) which are clarified in (15)-(18) respectively [19]:

$$SSE = \sum_{u=1}^{Z} (Target_u - Out_u)^2 \qquad (15)$$

$$MSE = \frac{1}{Z} \sum_{u=1}^{Z} (Target_u - Out_u)^2 \qquad (16)$$

$$MAE = \frac{1}{Z} \sum_{u=1}^{Z} |Target_u - Out_u| \qquad (17)$$

$$MAPE = \frac{1}{Z} \sum_{u=1}^{Z} \frac{|Target_u - Out_u|}{T_u} \qquad (18)$$

where:
Target: is the desired output values.
Out: is the current MLP output values.
u: is the counter of output neurons.
Z: is the number of output neurons.

Table II illustrates the statistical comparisons based authentication between our method and others for one line testing samples.

According to Table II, the proposed method in this paper attained best results, especially for the minimum values of all errors which contributes to more accurate authentication. As it could be seen from the statistical error values our results are much more better than others in every case and outperforms these methods.

Finally, samples of images after testing is given in Figs. 9 and 10. In this figure, it is clear that the differences between the known and unknown signature samples produced clear or distorted face images respectively.

Fig. 9 Sample of images after the MLP testing with known signature input samples

TABLE II
STATISTICAL COMPARISONS BASED AUTHENTICATION BETWEEN THIS WORK
AND OTHER PUBLISHED PAPERS

Reference	Statistical Errors in this work	Statistical Errors in [18]	Statistical Errors in [19]	Statistical Errors in [20]	Statistical Errors in [21]
Min (MSE)	3.4025×10^{-6}	---	0.00064	---	0.00053
Mean (MSE)	2.4414	BR*: 8.5079×10^{-4} AR*: 28.6403	0.00050	BR*: 0.0010 AR*: 48.9022	0.00038
Min (MAE)	0.0010	---	Mean: 0.01796 Max: 0.02553 Min: 0.00861	---	0.01482
Mean (MAE)	0.4969	---	Mean: 0.01993 Max: 0.03311 Min: 0.01134	---	0.01718
Min (SSE)	0.0227	---	0.58511	---	1.12700
Mean (SSE)	$1.6260 \times 10^{+4}$	BR: 1.3613 AR: $4.5825 \times 10^{+4}$	0.45800	BR: 3.4182 AR: $1.6040 \times 10^{+5}$	0.79380
Min (MAPE)	0.0142	---	Mean: 0.03376 Max: 0.04795 Min: 0.02486	---	0.03664
Mean (MAPE)	9.3832	0.973047	Mean: 0.06139 Max: 0.07168 Min: 0.05204	2.543423	0.04367

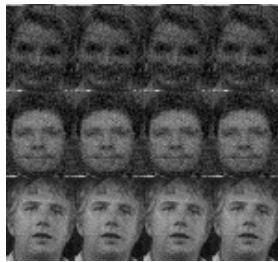*BR= Before Rescaling , *AR= After Rescaling

Fig. 10 Sample of images after the MLP testing with unknown
signature input samples

VI. CONCLUSION

A novel approach to predicting physical biometric from behavioural biometric is investigated in this paper. The results indicated that there is an interesting relationship between them by using the artificial neural network technique.

Feature extraction accomplished for the signature characteristics by segmenting the data into multiple windows resolutions. Then, the coefficient of variance values have been taken to each window and prepared for using by the MLP. The face image details are maintained after choosing the appropriated pixels. This reduces the effort to recognize people. The weights of the neural networks are collected in database files after the training part. Hereafter, the weights are used later in the testing stage to check the accuracy of this method. The results are compared with published work and is shown to be more efficient in all the most statistical measures shown.

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