



POTENTIALS OF ONE STEP SECANT AND FLETCHER-POWELL CONJUGATE GRADIENT BACK PROPAGATION ALGORITHMS FOR MULTIMODAL BIOMETRIC RECOGNITION APPLICATIONS

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Abstract

There has been an increased interest in reliable methods of biometric identification due to the growing emphasis on security and the increasing prevalence of identity theft. A multimodal system which combines several physiological traits of an individual could improve the security level. Most commercial biometric systems use artificial neural network (ANN) techniques due to their robustness to parameter changes. The performance of such a system depends on the learning algorithm. In this paper, the potential of Fletcher Powell Conjugate Gradient (FPCG) and One Step Secant (OSS) backpropagation learning algorithms for a multimodal hand geometry recognition application is considered and analysed. The effectiveness of these algorithms is assessed using the mean square error, image gradient, error histogram, and regression. Simulation results show that the FPCG algorithm has better performance than the OSS algorithm in terms of the mean square error, regression, and image gradient. The mean square error due to the FPCG is lower than that of the OSS algorithm. This indicates that there is about 76% improvement in the mean square error if the FPCG algorithm is selected over the OSS. Also, the regression analysis shows that the FPCG algorithm is more accurate than the OSS algorithm. However, in terms of speed of convergence, the OSS algorithm has the lowest number of epochs to attain best performance. Among these two backpropagation algorithms, the FPCG is considered more suitable for multimodal hand geometry identification.

Keywords: Access control, ANN, backpropagation, biometrics, FPCG, OSS

Introduction

Advances in computing and information technology have made automated identification of individuals based on their biological, physiological, or behavioural traits a feasible approach for access control. In recent times, there has been an increased interest in reliable methods of biometric identification due to the growing emphasis on security and the prevalence of identity theft. Biometric identification is the process of identifying a person using distinctive physiological and/or behavioural traits. Because each person has unique physiological and behavioural characteristics, biometric identification is intrinsically more reliable (Jain *et al.*, 2020). Much better security is provided by biometric identification systems than by password and number systems because they use physiological features to verify a person's identity (Hu *et al.*, 2018). Various approaches to biometric systems have been introduced in the past. As shown in Figure 1, some of

these approaches make use of recognitions for fingerprints, faces, iris, retina, voices, signatures, gaits, keystrokes, and hand geometry (Nguyen *et al.*, 2017; Abed, 2017; Hezil *et al.*, 2018; Piciuccio *et al.*, 2018; Abozaid *et al.*, 2019; Wang *et al.*, 2020; Sepas-Moghaddam *et al.*, 2020; Sancen-Plaz *et al.*, 2020). Facial images, hand geometry, finger prints, and retinal patterns are the most widely used for biometric access control systems. Biometric features such as faces or fingerprints can be stored on a microchip in a credit card. Arguably, fingerprint is the single most widely used method for individual identification and authentication (Sarfaz, 2019). The human hand not only possesses distinct features for gender information, it is also considered one of the primary biometric traits used to identify a person. An advantage of hand images is that they are usually captured in a controlled position, unlike face images, which are usually unconstrained (Afifi, 2019).

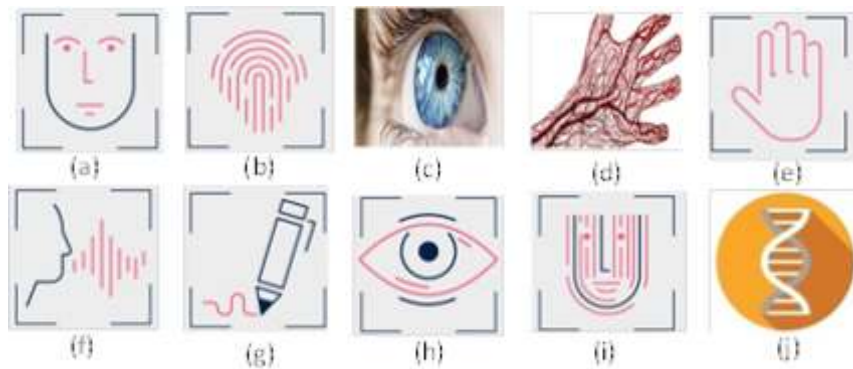


Figure 1: Human traits used for biometric recognition (a) face recognition (b) fingerprint (c) iris recognition (d) palm vein recognition (e) hand geometry (f) voice recognition (g) hand writing (h) retina recognition (i) face thermogram (j) DNA matching

For identity recognition, the hand geometry integrates several features of the palm and fingerprint. Sometimes, using a single feature may not be accurate enough to allow for identification. The selected feature is not always readable, either. Therefore, multimodal systems, like those based on hand geometry, could overcome such limitations and achieve much greater security than single-feature systems (Frigchholz and Pieckmann, 2000; Iula and Micucci, 2022). Thus, a multimodal-based biometric system has been proven to offer higher identification accuracy as well as mitigate numerous spoof attacks (Khurshid and Selwal, 2020). They are increasingly being employed in various security applications. Numerous studies have been conducted recently on the multimodal recognition system (Frigchholz and Pieckmann, 2000; Prabu *et al.*, 2019; Velmuruson and Selverajon, 2019; Khurshid and Selwal, 2020; Haidan *et al.*, 2020; Iula and Micucci, 2022). In order to find a close enough match between biometric features of an individual, multimodal biometric identification often scans through a sizable database of biometric records (Hu *et al.*, 2018). Feature extraction of the hand geometry recognition system could be achieved using different machine learning algorithms. Due to their tolerance to parameter changes, artificial neural network (ANN) approaches are used in the majority of commercial hand geometry biometric systems (Abiodun *et al.*, 2018; ErKaymaz, 2020; He *et al.*, 2020).

ANNs use back-propagation or a similar gradient descent algorithm. It is significant to note that the effectiveness of such a system would be influenced by the learning algorithm employed. Increasing the effectiveness of training and learning for neural network-based algorithms is a current research topic. This study considers and evaluates the potentials of Fletcher-Powell Conjugate Gradient (FPCG) and One Step Secant (OSS) backpropagation learning

algorithms for a multimodal hand geometry recognition system. The performance of these algorithms is assessed using the mean square error, image gradient, error histogram, and regression. The paper is structured as follows: Section 2 presents the methods used in this paper, which include the accessed backpropagation algorithms, the captured sample images as well as the performance metrics; in Section 3, the analysis of the results obtained; and Section 4 concludes the paper.

Materials and Methods

As shown in Figure 2, the hand geometry verification system has three main parts: enrolment, identification, and verification. Hand images are pre-processed in the enrolment phase to produce numerical features, which are then enrolled with an ID in the identification phase and trained using an artificial neural network. Finally, in the verification phase, the system compares the newly-input data to the data that has already been stored in the database. The input variables to the system are pictures of hand images obtained from the College of Engineering Pune (COEP) Palm Print Database. The images utilised in the research were taken from 150 people, each with 5 pixels. For image processing, the images are stored in the Joint Photographic Experts Group (JPEG) format in the database. The images went through a pre-processing phase, which includes conversion to grayscale images, noise removal, and edge detection. The grayscale image conversion helps to cancel the hue saturation information in the images while keeping the luminance information. Noise in the image was removed to prevent disparity between the actual palm and the captured image. During the edge detection process, only the edges of the image were used to extract geometric elements of the hand. The edge detection method is used to find points in a digital image with discontinuities in brightness.

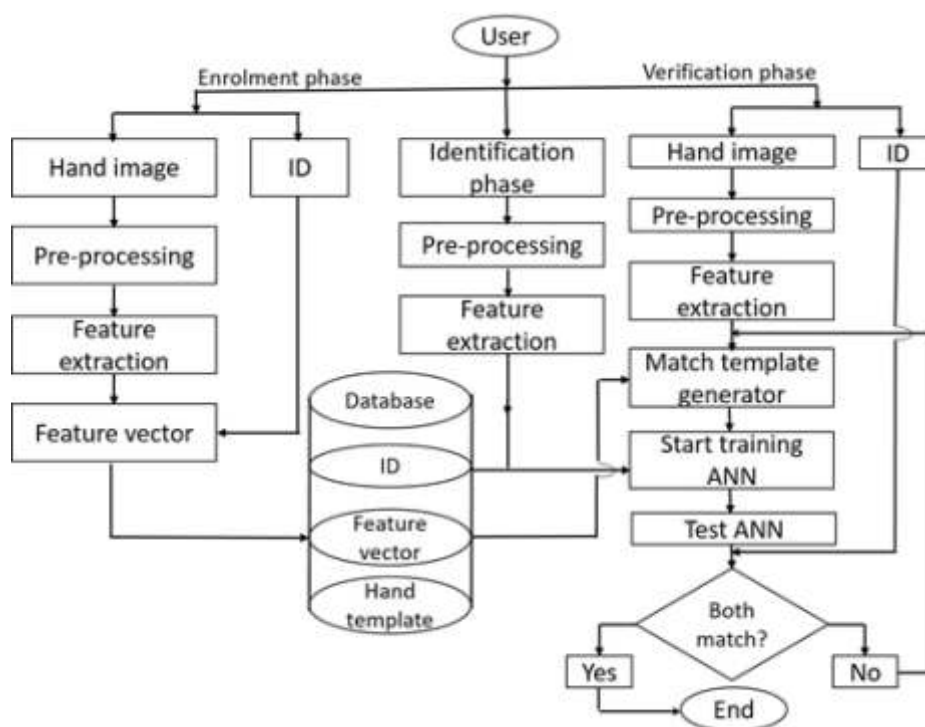


Figure 2: Hand geometry system

Some of the features extracted from the hand geometry are finger width (FW), finger length (FL), finger sub-length (SL), palm width (PW), palm length (PL), and hand length (HL) as shown in Figure 3. The features

were trained using two backpropagation algorithms, which are the FPCG and OSS algorithms. These algorithms are available in the MATLAB environment.

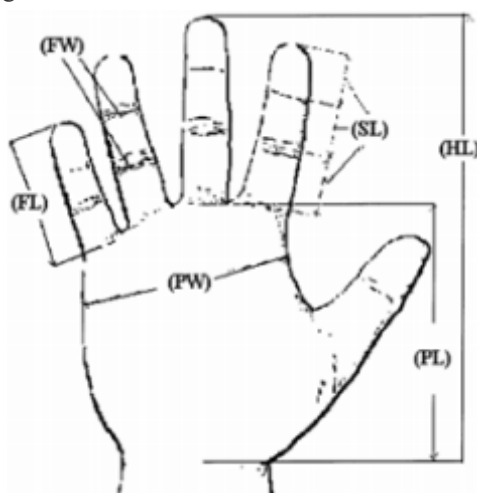


Figure 3: Some of the extracted hang geometry features

Backpropagation Algorithm

The Backpropagation learning algorithm (BPLA) is a simple iterative algorithm that usually performs well, even with complex data. Unlike other learning algorithms, such as Bayesian learning, it has good computational features when working with large scale data (Solikhun *et al.*, 2020). The input layer, output

layer, and hidden layer make up the conventional structure of a backpropagation artificial neural network (BPANN), as shown in Figure 4. The input layer is the one where the data is introduced to the network. The data is processed in the hidden layer while results of the given input are produced at the output layer (Huang and Wu, 2017; Wanto *et al.*, 2017; Febriadi *et al.*, 2018).

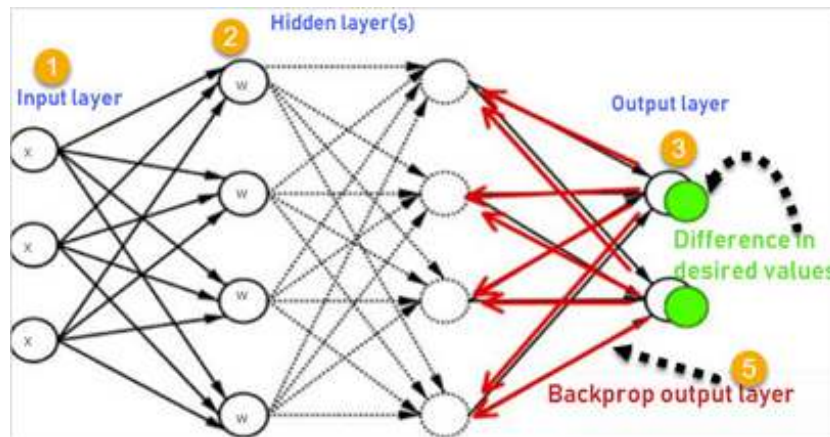


Figure 4: Backpropagation ANN

BPLAs employ the gradient-descent search approach to modify the connection weights during the learning phase in order to decrease the ANNs' inaccuracy (Solikhun *et al.*, 2020). Each neuron's output is the sum of the neuronal counts from the three previous levels, multiplied by the associated weights. With the use of activation function calculations, the input values are transformed into output signals. During the learning process, the backpropagation algorithm is used to update the weights and biases of a neural network. The weights and biases are updated using the two gradient descent algorithms (that is, FPCG and OSS). By propagating the computation backwards from the output layer to the first hidden layer, the gradient is obtained. As long as the new inputs are similar to the training inputs, a backpropagation network that has been properly trained can generalize to produce good outputs on inputs that it has never "seen" (Silaban *et al.*, 2017; Setti and Wanto, 2019; Lillicrap *et al.*, 2020). The performance of these algorithms was evaluated and the results are presented.

Fletcher-Powell Conjugate Gradient

This meets the curvature criterion by finding the solution to the secant equation that is closest to the current estimate. Following Fletcher-Reeves updates, the Fletcher-Powell Conjugate Gradient technique modifies weight and bias. The Conjugate Gradient approach developed by Fletcher and Reeves is a version of the Fletcher-Reeves update (Abid *et al.*, 2006; Liu *et al.*, 2016). The method can train any network if the weight, net input, and transfer functions have derivative functions. The derivatives of performance with respect to the weight and bias vectors M are calculated via backpropagation. Each vector M_i is adjusted according to Equation (1) (Liu *et al.*, 2016).

$$M = M + \alpha(dM) \quad (1)$$

where, dM is the search direction and α is the parameter used to minimise the search direction's performance. The line search function "searchFcn" is used to locate

the minimum point. In succeeding iterations, the search direction is computed from the new gradient and the previous search direction according to Equation (2) (Liu *et al.*, 2016).

$$dM = gM + \beta(dM) \beta k g_k \quad (2)$$

where, gM is the gradient. The parameter β can be computed in several different ways. For the Fletcher-Reeves variation of conjugate gradient it is computed using Equation (3) (Liu *et al.*, 2016).

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \quad (3)$$

where, $g_{k-1}^T g_{k-1}$ is the norm square of the previous gradient and $g_k^T g_k$ is the norm square of the current gradient.

One Step Secant Algorithm

The one step secant technique works on the assumption that at each iteration, the identity matrix was the previous Hessian. Thus, the entire Hessian matrix is not stored (Nguyen *et al.*, 2020). The additional benefit of this is that it eliminates the need to compute the matrix inverse in order to calculate the new search direction (Upadhyay, 2013; Nguyen *et al.*, 2020). The method may train any network using the function "trainoss" in the MATLAB environment if the weight, net input, and transfer functions all have derivative functions. Backpropagation is used to calculate the performance derivatives with respect to the weight and bias vectors M . As in conjugate gradient algorithms, each vector M_i is modified in accordance with Equation (1), and the line search feature is used to determine the minimum point. The performance gradient's inverse is represented by the first search direction. According to Equation (4) (Ginantra *et al.*, 2021), the search direction is computed in subsequent iterations using the current gradient and the changes in the weights and gradients from the previous iteration.

$$dM = -gM + Ac[M_{step} + bc(dgM)] \quad (4)$$

where gM is the gradient M_{step} is the change in the weights of the previous iteration, dgM is the change in the gradient from the last iteration whereas Ac and bc are the combinational scalar products of gM , M_{step} and dgM .

When the maximum number of epochs is completed or the performance gradient reaches the minimum gradient, training is terminated. The maximum deviation between all training functions is provided by the one-step secant (TrainOSS) approach. The OSS advantage is in determining the new search's direction rather than the inverse matrix (Ginantra *et al.*, 2021).

Data used

The data for this study were obtained from the Palm Print Database at the College of Engineering, Pune (College of Engineering, Pune-411005). The dataset includes various images of the hand geometry that were taken using a desk scanner without pegs. The resolution of the image is 1600 by 1200 pixels. The database consists of a total of 1344 hand images pertaining to 168 people, collected over a period of one year. Each algorithm was trained using 70% of the hand images. Out of the remaining 30%, 15% was used for testing and another 15% for validation. Samples of some of the hand images stored in the database are shown in Figure 5.



Figure 5: Samples of the hand images in the dataset

Performance Metrics

The performance of both algorithms was evaluated based on their mean square error, image gradient, error histogram, and regression analysis. The *MSE* measures the average of the square of the errors. The *MSE* is computed as

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (5)$$

where n denotes the number of data points,

and Y_i and $\hat{Y}_i$ denote the vector of the observed

and predicted values respectively. It is utilized to determine the level at which a model fits the data well.

The potentials of each algorithm were also accessed through their image gradients (using the Sobel filter method), which is a measure of the directional change in the intensity of an image. The error histogram metrics measure how the errors from the neural network on the testing instance are distributed, while the regression plot gives an idea of how close the output

from the model is to the actual target values. The simulation of the algorithms and the analysis of the performance metrics were carried out on the Windows 10 (64-bit) operating system with an i5 processor and 4 GB of RAM. All training functions used are coded in MATLAB software using the ANN toolbox.

Results and Discussion

Fig. 6 shows the variation of the MSE by epoch for training, validation, and testing for the FPCG (Fig. 6(a)) and OSS algorithm (Fig. 6(b)). Considering Fig. 6(a), during the training phase, a MSE of 1.75×10^{-4} at 25 iterations was obtained, with the best validation performance being 1.989×10^{-2} at 40 epochs. The validation error is lowest at the epoch of 40. After the training phase, the MSE reaches 1.63×10^{-2} at 46 epochs, with the best validation performance being 1.989×10^{-2} at 40 epochs. Considering Fig. 6(b), for the OSS algorithm, a MSE of 0.789 was obtained at 15 iterations during the training phase, with the best validation

performance being 8.2154×10^{-2} at 21 epochs. This algorithm has the lowest validation error at the 40th epoch. After the training phase, the MSE reaches 2.82×10^{-2} at 28 epochs, with the best validation performance being 8.2154×10^{-2} at 21 epochs. Comparing the potentials of both algorithms, the results show that the OSS algorithm converges faster

than the FPCG algorithm. The OSS takes about 21 epochs to reach its best validation performance, while the FPCG algorithm takes about 40 epochs to reach its best validation performance. Thus, in terms of the speed of convergence, the OSS performs better than the FPCG. Nevertheless, the FPCG algorithm has a better mean square error.

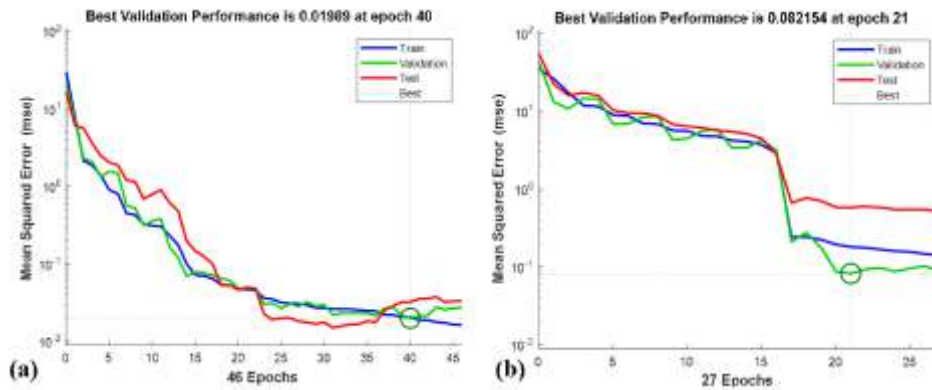


Figure 6: Mean square error (a) FPCG algorithm (b) OSS algorithm

The image gradient plot for both FPCG and the OSS algorithms is shown in Figure 7. The gradient coefficient varies with the number of epochs, as seen in Figure 7. For the FPCG algorithm (Figure 7(a)), at epoch 46, the final value of the gradient coefficient amounts to 1.5726×10^{-1} at epoch 13, we can see that the validation fail is 0 and validation check is equal to 6 after epoch 19. For the OSS algorithm (Figure 7(b)), at epoch number 46, the final value of the gradient coefficient is 1.3732 while at epoch 21, the validation failure of 0 occurs (epoch 13 for FPCG algorithm). Similarly, the validation check is equal to 6 after epoch 27, as against 19 epochs of the FPCG to achieve the same level of performance. Comparing the potentials of both algorithms, it is observed that the FPCG algorithm has a relatively lower image gradient coefficient than the OSS algorithm. A lower value of the image gradient

coefficient means that the algorithm has superior performance. The error histogram plot for the two algorithms is also discussed (see Figure 8). This metric is used to find the number of errors between target values and predicted values of training, validation, and testing datasets. For the FPCG algorithm (Figure 8(a)), the testing stage has the highest error around -0.04882, the validation stage has the highest error at -0.04882 and the training stage has the highest instances at error -0.04882. Considering the OSS algorithm (Figure 8(b)), the testing stage has the highest error around 0.3595, the validation stage has the highest error at 0.3595 and the highest number of instances at error 0.01886 and the training stage has highest instances at error 0.3595. The result indicates that the FPCG algorithm has a lower error bin than that of the OSS algorithm.

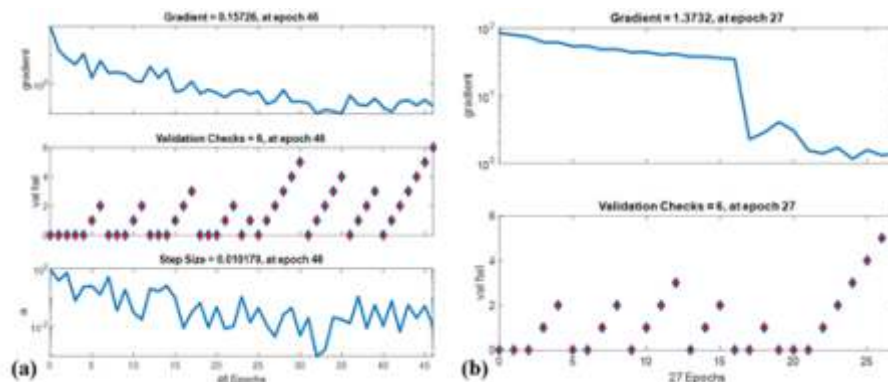


Figure 7: Image gradient for (a) FPCG algorithm (b) OSS algorithm

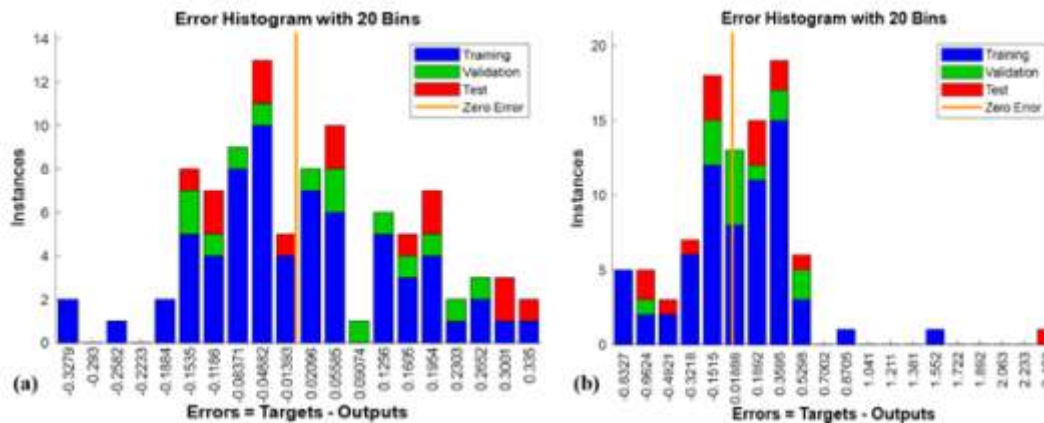


Figure 8: Error histogram plot for (a) FPCG algorithm (b) OSS algorithm

Figure 9 displays the regression plots for the predicted values of training, validation, and testing for the FPCG and OSS algorithms, respectively. This plot is used to find the relationship between the predicted and actual values. The “target” values in the plot are the actual dataset, whereas the “output” is the predicted values obtained from each of the algorithms. As can be observed in Figure 9(a) and Figure 9(b), there is a good agreement between the predicted values and the actual ones. This means that the algorithm provides a performance where the predicted value perfectly fit the target values. This performance is considered to be relatively better. According to Figure 9(a), which depicts the regression analysis for the FPCG algorithm, the regression value for training is approximately 0.99879, while the values for validation and testing are 0.99867 and 0.9989, respectively. A regression value of

0.99872 was obtained for the whole dataset (that is, training, testing, and validation). This gives a network average regression percentage of 99.87% for the FPCG. This is closer to the 100% benchmark for excellent performance that any algorithm could achieve when regression is considered. For the OSS algorithm shown in Figure 9(b), the training dataset yielded a regression value of 0.98856, the validation dataset yielded a value of 0.99591, and the testing dataset yielded a value of 0.96917, while the entire dataset yielded a value of 0.9865. This amounts to a network average regression percentage of 98.65%. Comparing both algorithms, though both algorithms performed better as the regression value is very close to 1 or 100%, the FPCG algorithm has superior performance over the OSS algorithm.

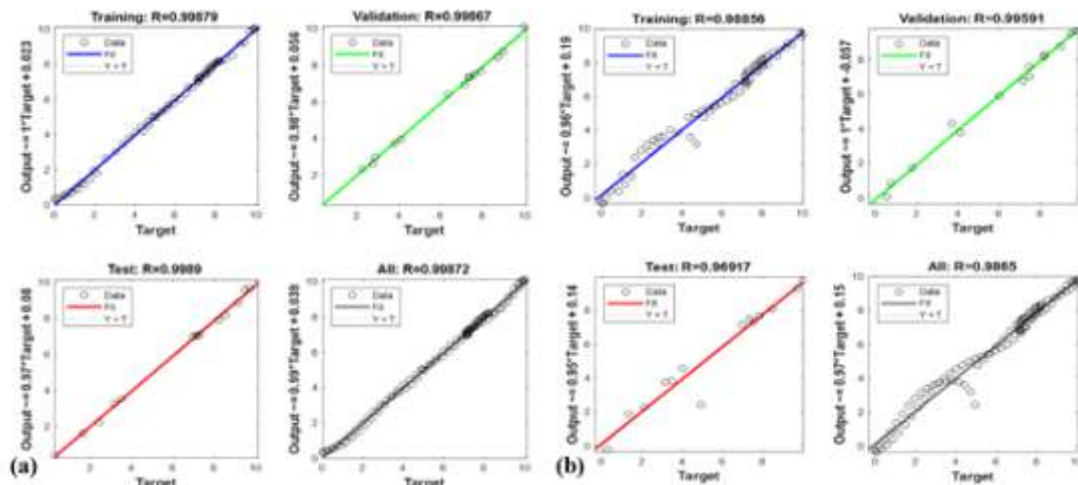


Figure 9: Regression plot for (a) FPCG algorithm (b) OSS algorithm

Conclusion

A multimodal hand geometry-based biometric identification utilizes several features of the palm and finger prints of an individual. It typically scans a large-scale database of biometric records of hand images to find a close enough match for an individual. In this paper, feature extraction of the hand geometry was trained using Fletcher-Powell conjugate and one-step gradient ANN backpropagation algorithms. The potentials of these algorithms was evaluated for multimodal biometric applications. Empirical results showed that for multimodal hand geometry recognition applications, the FPCG has a relatively better performance than the OSS algorithm in terms of the mean square error, regression, and image gradient. The only advantage the OSS algorithm has over the FPCG algorithm is its faster convergence. It thus has the lowest number of epochs to attain best performance. However, the mean square error due to the FPCG algorithm is relatively lower than that of the OSS algorithm. The mean square error due to the FPCG algorithm is less than that of the OSS. Also, the regression provides the best fit and is thus more accurate than the OSS algorithm. Among these two backpropagation ANN algorithms, the FPCG is considered more suitable for multimodal hand geometry identification.

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