Bi-Modal System Using SVM (Support Vector Machine) and MLP (Multilayer Perceptron) -Proposed

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Abstract
In this era of high technological advancement, the need to identify an individual especially in the developing countries has long been an attractive goal. The necessity to secure an environments, devices and resources due to the increasing rate of crime has led to the proposal of this research. Iris modality has become interesting as an alternative approach to reliable visual recognition of persons due to its distinctive characteristics, as well as fingerprint modality for its innumerable advantages. Therefore a bi-modal biometric system using Qualitative SVM (Support Vector Machine) and MLP (Multilayer Perceptron) for classification has been proposed in this research. Performance analysis of these modalities will be carried out with each model. The designed models will be duly implemented using JAVA programming Language as a frontend and Access database as a backend respectively.
Keywords: Biometric, Bimodal system, Iris modality, fingerprint modality, Support Vector Machine and Multilayer Perceptron.

1. Introduction

To control an access in order to protect a particular areas or resources, a dependable personal identification infrastructure is essential in this technological advanced era. The accustomed ways of distinguishing the identity of an individual by using passwords, pins or cards are not altogether dependable, because they can be lost, forgotten, stolen, revealed, or transferred (Zhang, 2000). Biometric technology, which is based on physical and behavioural features of human body such as face, fingerprint, hand shapes, iris, palm-print, keystroke, signature and voice, (Lim et al., 2001, Zhang, 2000, Zhu et al., 1999) is considered an alternative to existing systems in a great deal of application domains.

Bi-modal biometrics refers to the use of more than one biometric feature for person recognition. A bi-modal biometric system encompasses the necessary processing required to incorporate the chosen more than one biometric characteristic into the authentication procedure. The use of more than one biometric feature has greatly increased the reliability of the person authentication process. Bi-modal biometric systems help to achieve an increase in performance that may not be possible using a single biometric indicator (Souheil, 2007). It is very difficult for an impostor to concurrently impersonate the various character traits of a rightful user due to the emergence of more than one biometric system (Ross et al., 2001).

Each of the biometric technology has its own advantages and disadvantages based on their usability and security (Hasimah and Momoh, 2011). Among the various traits, iris recognition has attracted a lot of attention. Iris is an internal (yet externally visible) organ of the eye, which is well protected from the environment and its patterns are apparently stable throughout the life. The iris consists of variable sized hole called pupil. It has the great mathematical advantage that its pattern variability amongst people is great (Daugman, 2002). Every iris has fine unique texture and does not change over time. Because of high randomness in the iris pattern, it has made the technique more robust and it is very difficult to deceive an iris pattern (Daugman, 2003). Unlike other biometric traits, iris recognition is the most accurate and non–invasive biometric for secure authentication and positive identification (Masek, 2003).

Among all the biometric techniques fingerprint identification is also the most widely used biometric identification form. It has been used in numerous applications (Terje, 2012). Each print has an exclusive owner, and there has never been two individuals recorded with the same print (including an identical twins) (Eckert, 1996; FIDIS, 2006). The fingerprint ridges never change, from birth until death – and – no matter what happens; they will always reappear within short period of time (Salter, 2006; Wayman et al, 2005)

1.1 Literature Reviewed

Yang et al (2002) in their work suggested that fingerprints are the ridge and furrow patterns on the tip of the finger and have been used extensively for personal identification of people. The quality of the ridge structures in a fingerprint image is an important characteristic, as the ridges carry the information of characteristic features required for minutiae extraction. Fingerprints have many conspicuous landmarks and any combination of them could be used for establishing a reference point. The reference point of a fingerprint is defined as the point of maximum curvature of the concave ridges in the fingerprint image.

Chan et al (2004) proved that the minutiae can be extracted by scanning the local neighbourhood of each ridge pixel in the image using a 3 x 3window. The crossing number (CN) value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighbourhood. Once the reference point is located, all minutiae extracted from a master fingerprint image can be aligned with the reference point to generate a circular sub region in the original image.

Hasimah and Momoh (2011) developed an iris recognition system, which was tested using database of grayscale eye images in order to verify a person. The advantages of iris recognition systems offering reliable and effective security in the present day brought about the emergence of this research. Segmenting method was used to localize the iris region from the eye image, firstly. Then the localized iris image was normalized to eliminate dimensional inconsistencies between iris regions using Daugman's rubber sheet model. Finally features of the iris region were encoded by convolving the normalized iris region with 1D Log-Gabor filters and phase quantizing the output in order to produce a bit-wise biometric template. The Support Vector Machine was adopted as classifier in order to develop the user model based on his/her iris code data. Experimental study using the Chinese Academy of Sciences–Institute of Automation (CASIA database was carried out to evaluate the effectiveness of the proposed system. Based on obtained results, SVM classifier produces excellent False Accept Rate (FAR) value for both open and close set condition. The proposed system seems in a good level of security. However, further study has to be done to improve level of usability by reduce the value of False Reject Rate (FRR). In this research only one classifier was utilized.

Sangeetha and Radha (2012) proposed a New Framework for Iris and Fingerprint Recognition Using SVM Classification and Extreme Learning Machine Based on Score Level Fusion. The disadvantages of uni-biometric systems (based on single biometric trait) that has several drawbacks like noisy sensor data, non-universality or lack of distinctiveness of the biometric trait, unacceptable error rates, and spoof attack give rise to this research. Impersonate. The individual scores of two traits, iris and fingerprint were combined at the matching score level to develop a multimodal biometric authentication system. K-mean clustering was used to searching the database. Fusion at the score level is a new technique, which has a high potential for efficient consolidation of multiple unimodal biometric matcher outputs. Support vector machine and extreme learning techniques were used in this system for recognition of biometric traits. In this, the Fingerprint-Iris system provides better performance, and comparison of support vector machine and extreme learning machine based on score-level fusion methods was obtained. There is no performance analysis of each modality using the two models.

Terje (2012) developed a hybrid technique for classification of fingerprint identification to decrease the matching time. Since the current work in this field concentrates on reducing the computation time for feature extraction and matching , so he was enthused to develop algorithms which are robust to noise in the fingerprints and are able to deliver accuracy in real time. For classification, a Support Vector Machine (SVM) and a Multi-Layered Perceptron (MLP) network were described and used. The fingerprint patterns generated were based on minutiae extraction from a thinned fingerprint image. The given fingerprint database was decomposed into four different sub-classes. Two different classification regimes were used to train the systems to do correct classification. The classification rate was estimated to about 87.0 % and 88.8% of unseen fingerprints for SVM and MLP classification respectively. The classification rate of both systems was only differing marginally. Compared to SVM, MLP network was able to do a slightly better classification (Kristensen, 2010). However, it was known that a SVM classifier becomes better when the dimension of the input space becomes higher. The main objection by the method used so far was that the number of training samples was too small compared to the number of features in the FingerCode vector. With this reason, good results compared to the results in the literature could not be achieved. To test the effectiveness of the systems, there is need for more than one modality for authentication.

Basha et al (2012) developed a Multimodal Person Authentication using Qualitative SVM with Fingerprint, Face and Teeth Modalities**.** The need to secure handheld devices like PDA, smartphones etc brought about the research because they increasingly become the target for theft for not only its physical value but also for the invaluable data like banking passwords, email accounts and, etc. Fingerprint, Face and Teeth regions were detected using Ada Boost algorithm and verified using EHMM technique. Finally, the normalized scores of all the unimodal systems were fed into qualitative SVM classifier for reject/accept the claim. One model was used to classify the features. The data used was too small.

Vijayaprasad et al (2010) developed a partial fingerprint recognition using support vector machine, a novel partial fingerprint matching approach that uses global minutiae matching and the support vector machine was presented. Global minutiae matching algorithm was used to record the matching pair and their feature vectors were used to generate a model file which was used for classification. The traditional minutiae-based matching approach was studied as a classification approach by using support vector machine. Fingerprint verification competition databases were used for evaluation. Results from the experiment showed 98.5% of matching compared to 97.6% using flow network-based approach. There is need to verify the model with different databases which consist of large data and addressing strong enhancement methods.

Sim (2012) developed a robust automated algorithm for real time iris detection in higher level security purpose with high recognition rates in varying environment. Haar cascade based algorithm was applied for fast and simple face detection from the input image. The face image is then being converted into grayscale image. After that, the iris candidates were extracted from the intensity valleys from the detected face. Costs of each iris candidates were calculated. The iris candidates were paired up and the cost of each possible pairing was computed by a combination of mathematical models. After that, these irises pair was treated as information for system to continue the tracking it in the continuous frame. The algorithm was able to work on complex images without constraints on the background or surrounding lighting. The system runs slower in higher resolution images through many times of testing which affects the real time performance because the system cannot capture every frame and cause the learning rate to became low.

Ahmad (2009) developed an Iris Recognition Using Discrete Cosine Transform and Artificial Neural Networks. For an efficient Iris recognition system to be developed, the discrete cosine transform for feature extraction and artificial neural networks for classification was employed. The iris images used in this system were obtained from the CASIA database. An iris recognition system that produces very low error rates was successfully designed. There is need to use 3-layer structure for better performance for ANN.

2. Proposed Bimodal System

In the bimodal system there will be an acquisition, processing and matching of features from the two modalities as follows:

2.1. Iris Modality

In iris modality, there will be an image acquisition, image pre-processing and matching. In image acquisition, a high–quality image of the iris has to be captured in order for the system to work well. Since images captured using infrared camera has good quality with high distinction and low reflections then, infrared camera will be used to capture iris image.

In image pre-processing, there will be an image localization and segmentation; image normalization; Feature extraction or encoding. In iris recognition system, the first stage will be to isolate the actual iris region in a digital eye. The purpose of iris localization is to confine an acquired image that match up to an iris. Eyelids and eyelashes blocking the upper and lower parts of the iris region will be cut off from the detected iris image by regarding them as noise because they will reduce the performance of the system. Daugman (2002) integro-differential operator to detect the centre and diameter of the iris and the differential operators to detect the pupil will be used. That is

$$\max\,(r, x_o, y_o) \left| G_\sigma(r) * \frac{\partial}{\partial_r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right| \tag{1}$$

where *I(x, y)* is the eye image, *r* is the radius to search for, $G_\sigma(r)$is a Gaussian smoothing function, *s* is the contour of the circle given by r, x_o, y_o - defining a path of contour integration (Masek, 2003).

In iris normalization, the localized iris part will be transformed into polar coordinates system so that it has fixed dimensions and also to overcome imaging inconsistencies. Using Daugman Rubber Sheet Model each point within the iris region will be remapped to a pair of polar coordinates (r, θ) where r is on the interval [0, 1] and θ is angle [0, 2π]. The remapping of the iris region is modelled as,

$$I\big(x(r,\theta), y(r,\theta)\big) \rightarrow I(r,\theta) \tag{2}$$

With

$$x(r,\theta) = (1 - r)x_p\,(\theta + r\,x_I\ (\theta)) \tag{3}$$

$$y(r,\theta) = (1 - r)y_p\,(\theta + r\,y_I\ (\theta)) \tag{4}$$

where I(x, y) is the iris region image, (x, y) are the original Cartesian coordinates, (r, θ*)* are corresponding normalized polar coordinates, and x_p, y_p and x_I, y_I are the coordinates of the pupil and iris boundaries along the θ direction.

In Feature extraction/encoding, in order to recognize the individuals accurately, the most discriminating features that present in the region will be extracted. Only the important characteristics of the iris will be encoded. The

Masek's algorithm will be used for feature encoding by convolving the normalized iris pattern with 1D Log-Gabor wavelets. Log-Gabor filters are created using,

$$G(f) = exp\left[\frac{-(\log(f/f_0))^2}{2\log(\sigma/f_0))^2}\right] \quad (5)$$

where f_o represents the centre frequency, σ gives bandwidth of the filter.

In Matching, to verify a person's identity, the calculated iris template needs to be matched with the stored template. Matching algorithm that will be used as pattern matching method to verify a person's identity based on the iris code is Support Vector Machine and Multilayer Perceptron.

2.2 Fingerprint Modality

In fingerprint modality, there will be an image acquisition which involves enrolment and collections of various data using a multi-spectral optical imager.

Extraction of the necessary features from the captured image and the processing of these features to obtain brief data which will assist in taking sensible decisions will be done through the following processes: fingerprint minutiae enhancement, minutiae extraction, pattern recognition and pattern matching.

During image enhancement, there will be an image segmentation which involves the separation of foreground region from the background of the captured image. Then image normalization which is used to standardize the intensity values in an image by adjusting the range of grey level values so that it lies within a desired range of values. Image Binarisation or thinning will be done after the application of Gabor filter to obtain its best performance threshold.

Fingerprint minutiae will be extracted from the enhanced images using mathematical model in (Iwasokun, 2012) modified from (Hong et al, 2006) and (Raymond, 2003). Database will be created for the extracted minutiae.

In Matching, to verify a person's identity, the calculated fingerprint template needs to be matched with the stored template. Matching algorithm that will be used as pattern matching method to verify a person's identity is SVM and MLP.

2.3 Fusion of Extracted Features from two Modalities

Score level fusion which involves the combination of information obtained from individual modalities will be used. Since the scores generated by a biometric system can be either similarity scores or distance scores, one needs to convert these scores into the same nature.

There are different levels in which data can be fused in biometrics namely; sensor level, feature level and decision level. Based on different researches it has been found that the best data fusion is the feature level and will be employed in this research. Researchers believe that feature level fusion will result in accurate and robust authentication, because data at this level is closer to raw data than the subsequent fusion levels and maintains more discriminatory information than those levels (Ross and Jain, 2004). Feature extraction typically requires the selection of salient features, from the independent data sources, that best represent the entity and can provide recognition accuracy (Poh and Kittler, 2008).

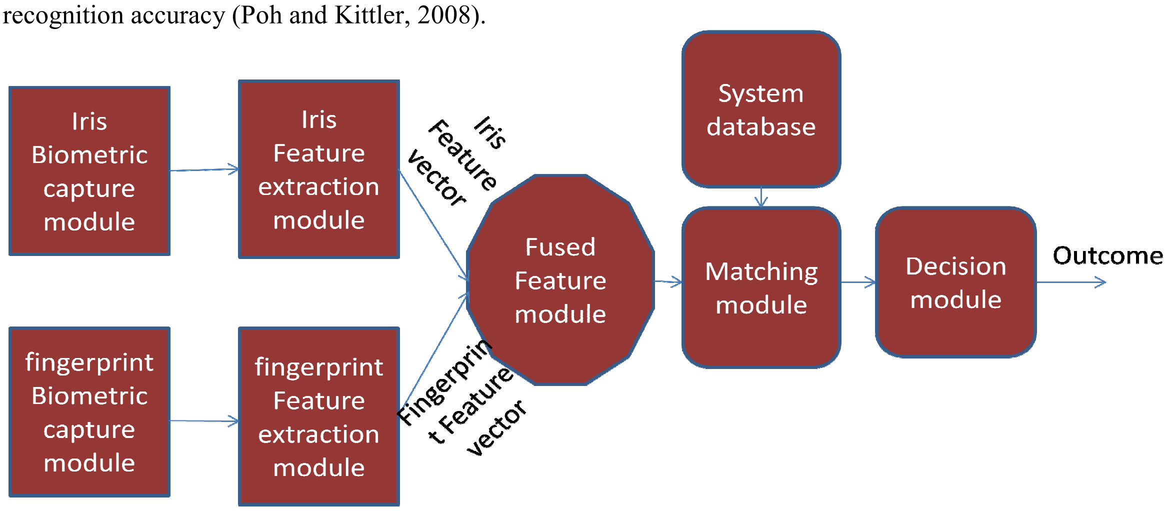

Figure 1: Feature level data fusion of iris and fingerprint data

2.4 Support Vector Machine as a Classifier

SVM is based on the principle of structural risk minimization (minimizing classification error). A SVM is binary classifier that optimally separates the two classes of data (Burges, 1998). Two major phases re required in the development of SVM as classifier. The first phase involves the determination of the optimal hyperplane which will optimally separate the two classes and the other is transformation of non-linearly separable classification problem into linearly separable problem. Figure 2 below shows linearly separable binary classification problem with no possibility of miss-classification data.

Let m and n be a set of input feature vector and the class label respectively. The pair of input feature vectors and the class label can be represented as tuples $\{m_i,n_i\}$ where i =1,2,…,N and n =±1. In the case of linear separable problem, there exists a separating hyperplane which defines the boundary between class 1 (labelled as n = 1) and class 2 (labelled as n = -1). The separating hyperplane is,

$$w.x + b = 0 \quad (10)$$

which implies

$$n_i(w.x + b) \geq 1, i = 1, 2, \ldots, N \quad (11)$$

We have several possible values of {**w**,b} that create separating hyperplane, but in SVM only hyperplane that maximizes the margin between two sets is used. Margin is the distance between the closest data to the hyperlane.

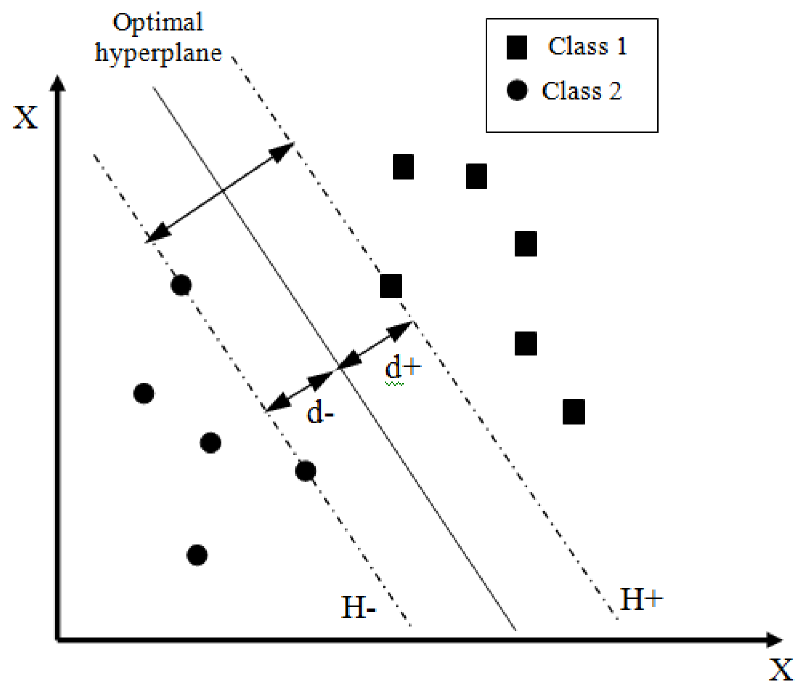

Figure 2: Support vector machine with linear separable data.

Considering the Figure 2 above the margins are defined as d+ and d-. The margin will be maximized in the case d+ = d−. Furthermore, training data in the margins will lie on the hyper-planes H+ and H-. The distance between hyperplane H+ and H- is,

$$d_+ + d_- = \frac{2}{\|w\|} \quad (12)$$

There is no training data which fall between H+ and H- as H+ and H- are the hyperplane which is the closest training data to the optimal hyperplane. This means the hyperplane that separates optimally the training data is the hyperplane which minimizes $\|w\|^2$ so that the distance of the equation (12) is maximized. However, the minimization of $\|w\|^2$ is constrained by equation (11). When the data is non-separable, slack variables, ξi, are introduced into the inequalities for relaxing them slightly so that some points are allow to lie within the margin or even being misclassified completely. The resulting problem is then to minimize,

$$\frac{1}{2}\|w\|^2 + C\left(\Sigma_i L(\xi_i)\right) \quad (13)$$

where C is the adjustable penalty term and L is the loss function. The most common used loss function is linear loss function, L(ξi) = ξi. The optimization of (13) with linear loss function using Lagrange multipliers approach is to maximize,

$$L_D(w, b, \alpha) = \sum_i^N \alpha_i - \frac{1}{2}\sum_{i=1}^N \sum_{i=1}^N \alpha_i \alpha_j y_i y_j \langle x_i . x_j \rangle \quad (14)$$

subject to

$$0 \leq \propto_i \leq C \quad (15a)$$

and

$$\sum_{i=1}^N \propto_i y_i = 0 \quad (15b)$$

where αi is the Lagrange multipliers. This optimization problem can be solved by using standard quadratic programming technique. Once the problem is optimized, the parameters of optimal hyperplane are,

$$w = \sum_{i=1}^N \propto_i y_i x_i \quad (15c)$$

α_i is zero for every x_i except the ones that lies on the margin. The training data with non-zero α_i are called support vectors. In the case of a non-linear separable problem, a kernel function is adopted to transform the feature space into higher dimensional feature space in which the problem become linearly separable.

2.5 Multi-Layered Perceptron as a Classifier

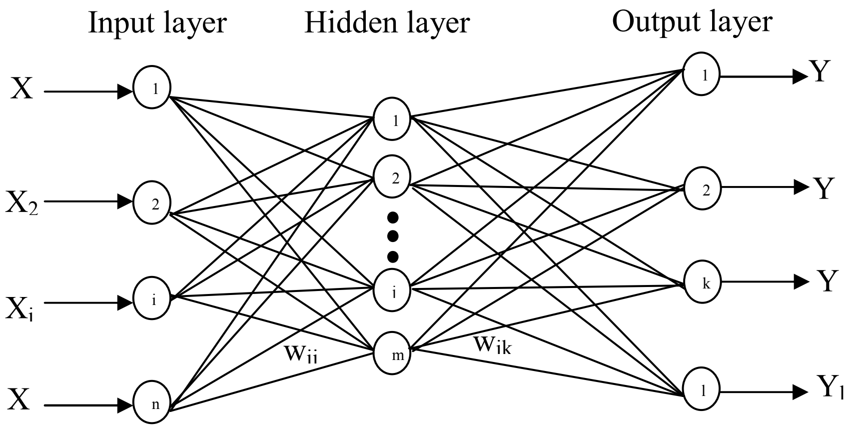

Figure 3: The architecture of the MLP network for classification of iris and fingerprint

A usual MLP consists of three layers of neurons: an input layer that receives external inputs, one hidden layer, and an output layer which generates the classification results as in figure 3 above.
The indices i, j, k here refers to the neurons in the input, hidden and output layers respectively. Input signal x_1, x_2,…,x_n are propagated through the network from left to right and error signals e_1,e_2,…e_l from right to left. The symbol w_{ij} denotes the weight for the connection between neuron i in the input layer and neuron j in the hidden layer, and the symbol w_{jk} the weight between neuron j in the hidden layer and neuron k in the output layer.
No computation is involved in the input layer unlike other layers; the procedure for the network operation goes does; when data are presented at the input layer, the network neurons run calculations in the successive layers until an output value is attained at each of the output neurons. The suitable class for the input data will be indicated by this output. Each neuron (as in figure 4) in the input and the hidden layers is connected to all neurons in the next layer by weighted connections. The neurons of the hidden layer compute weighted sums of their inputs and compares with a threshold. The resulting sums are used to calculate the activity of the neurons by applying a sigmoid activation function.
This process is defined as follows:

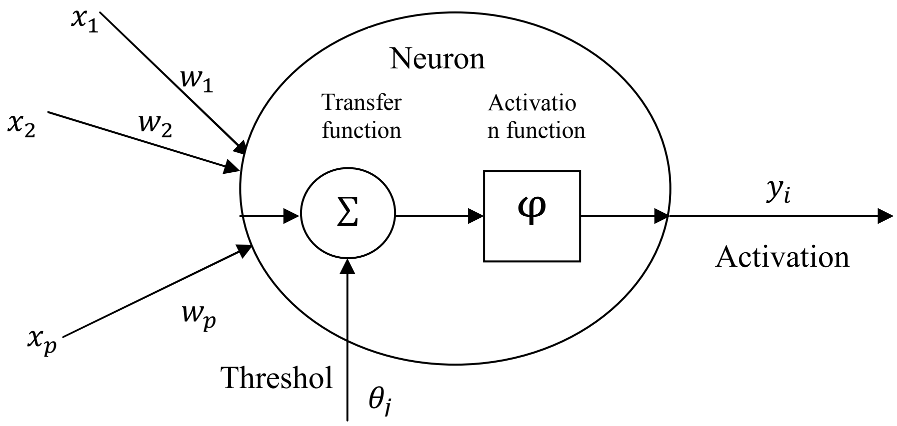

Figure 4: A neuron in the hidden or the output layer in the MLP.

$$T_j = \sum_{i=1}^{p} w_{ji} x_i + \theta_j \,, \qquad y_j = f_j(T_j) \qquad (16)$$

where T_j is the linear combination of inputs $x_1, x_2, \dots x_p$, and the threshold θ_j , w_{ji} is the connection weight between the input x_i and the neuron j, and f_j is the activation function of the jth neuron, and y_j is the output. The sigmoid function is a common choice of activation function. It is defined as:

$$f(t) = \frac{1}{1 + e^{-t}} \qquad (17)$$

The weights and the threshold defining the hyperplane input space into two subspaces is able to linearly separate a single neuron in the MLP. The weights define the direction of this hyperplane whereas the threshold term θ_j offsets it from origin.

To propagate error signals, it is starts at the output layer and work backward to the hidden layer. The error signal at the output of neuron k at iteration P is defined by;

$$e_k(P) = Y_{d,k}(P) - Y_k(P) \qquad (18)$$

Where $Y_{d,k}$ is the desired output of neuron k at iteration P and Y_k is the actual output at the same iteration.
To update the weight at the output layer the equation below is used;

$$w_{jk}(P+1) = w_{jk}(P) + \Delta w_{jk}(P) \qquad (19)$$

Where $\Delta w_{jk}(P)$ is the weight correction and is computed as;

$$\Delta w_{jk}(P) = \propto \times y_j(P) \times \delta_k(P) \qquad (20)$$

Where α is the learning rate, yj is the input pattern at the hidden layer and δk(P) is the error gradient at neuron k in the output layer at iteration P computed as;

$$\delta_k(P) = \frac{\partial Y_k(P)}{\partial X_k(P)} \times e_k(P) \qquad (21)$$

Where $Y_k(P)$ is the output network k at iteration P, $X_k(P)$ is net weighted input to neuron k at iteration P and $e_k(P)$ is the error at neuron output.
For sigmoid activation function equation (19) can be represented as

$$\delta_k(P) = \frac{\partial\left\{\frac{1}{1+e^{[-X_k(P)]}}\right\}}{\partial X_k(P)} \qquad (22)$$

$$= \frac{e^{[-X_k(P)]}}{\{1+e^{[-X_k(P)]}\}^2} \times e_k(P) \qquad (23)$$

Thus obtained

$$\delta_k(P) = Y_k(P) \times [1 - Y_k(P)] \times e_k(P) \qquad (24)$$

where

$$Y_k(P) = \frac{1}{1+e^{[-X_k(P)]}} \qquad (25)$$

The same procedure goes for the weight correction for a neuron in the hidden layer.
The MLP network uses the backpropagation algorithm (Rumelhart et al, 1986), which is a gradient descent method, for the adaptation of the weights (the backpropagation training parameters).

3. Conclusion

At the end of this research, bimodal biometrics authentication using Support Vector Machine (SVM) and Multilayer Perceptron (MLP) as a classifier has been designed. In the course of the design, the images from iris and fingerprint modalities will be acquired based on individual sensor module system. The features will be extracted from the acquired images and these features will be converted to the same nature, fused together for better recognition. Then to verify a person's identity, the features combined together will be match with the initial images stored in the database. The method employed for this is SVM and MLP as a classifier. The distinctive classification characteristic of the two classifiers has been shown in this research. The developed system will be implemented using JAVA programming Language as a frontend and Access database as a backend respectively, which may be employed in verification of an identity of an individual personality in the Banks, organizations, industries or people using ATM and other security departments in the country which will help reduce the rate of criminal activities or theft.

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