Distributed Optimization Model of Wavelet Neuron for Human Iris Verification

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***Abstract*—Automatic human iris verification is an active research area with numerous applications in security purposes. Unfortunately, most of feature extraction methods in human iris verification systems are sensitive to noise, scale and rotation. This paper proposes an integrated hybrid model among Discrete Wavelet Transform, Wavelet Neural Network and Genetic Algorithms for optimizing the feature extraction and verification methods. For any iris image, the wavelet features are extracted by Discrete Wavelet Transform without any dependency on scale and pixels' intensity. Besides, Wavelet Neural Network classifier is integrated as a local optimization method to solve the orientation problem and increase the intrinsic features. In solving the down sample process caused by DWT, each human iris should be characterized by a set of parameters of its optimal wavelet analysis function at a determined analysis level. Thus, distributed Genetic Algorithms, meta-heuristic algorithm, is introduced as a global optimization searching technique to discover the optimal parameter values. The details and limitation of this paper will be discussed where a comparative study should appear. Moreover, conclusions and future work are described.**

Keywords—Discrete Wavelet Transform (DWT); Wavelet Features; Wavelet Neural Network (WNN); Distributed Genetic Algorithms (GA); Human Iris Verification

I. Introduction

Since safety communication with others is a fundamental demand, verifying the direct measurements of some human parts, Biometrics, is the unique solution. In the field of human identification, iris verification is regarded as the most reliable and accurate biometric identification system [1]. The texture of the iris is relatively static and stable during the person's lifetime. Thus, iris texture is uniquely identifying individuals. The human iris, the part between the pupil and the sclera, has an extraordinary structure and provides many interlacing minute characteristics. The process of iris recognition depends on two consecutive phases, localization of the iris domain, as depicted in Figure1[2], and generation of the feature set of iris images. Hence, a convenient iris classifier should be used. Unfortunately, iris recognition suffers from the scale and rotation invariant problems, a certain fixed resolution, and non-regarding iris features during the stage of feature extraction. Moreover, the time complexity is taken in training by the iris classifier[2, 3, 4, 5].

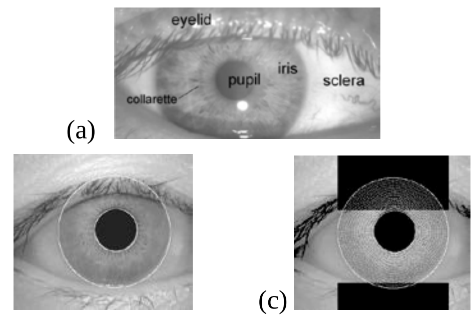


Fig. 1. Example of iris localization: (a) Original image. (b) Iris area localization. (c) Iris native area

In the recent past, some iris verification and recognition techniques have been developed. Based on local feature extraction process, many papers appear. Feng Hao et al. [6] proposed a practical and secure way to integrate the iris biometric into cryptographic applications. They represented the iris key as the repeatable binary string. Yaser Danial Khan et al. [7] extracted the iris feature based on the moments, and classified iris patterns based on k-means. Case-based Reasoning technique is combined in their classification technique. Huaqing Liang et al [8] proposed an iris recognition method based on iris's speckles characters. Mayank et al. [9] create a single high-quality iris image by enhancing the iris image globally. The iris image features are extracted based on 1-D log-polar Gabor transform and local topological using Euler numbers. Ma et al. [10] extracted the features of the iris by key local variations, spatial filter. Unfortunately, these techniques have unpromising results under intraclass variations ,different contrast and illumination settings, and miss the geometrical representation of the iris texture. Moreover, these techniques need much time to be processed and classified. On the other hand, spectral methods aim at describing the multi-resolution and directionality of periodic or almost periodic 2-D patterns in an image. Spectral methods refer to the frequency domain where feature are related to statistics of filter response [11]. K. Miyazawa [12] presented an efficient algorithm for iris recognition using phase-based image matching in 2D Discrete Fourier Transforms (DFTs). Unfortunately, DFTs perform poorly in practice, due to its lack of spatial localization. Some papers enhanced the extracted iris texture features based on Gabor [9, 13] where better spatial localization is provided. Unfortunately, Gabor filter is limited because there is no single filter resolution at which one can localize a spatial structure in iris texture. Because of the wide range of wavelet functions, Wavelet Transforms (WTs) have various resolutions that allow researchers to represent iris texture at the most suitable scale[14, 15, 2, 16]. But WT is still non-supportive to directionality and anisotropy [17]. As the result of the short in WT, each human iris should be characterized by a set of parameters of its optimal wavelet analysis function at a determined analysis level. Moreover, a suitable classifier should be combined to reduce the False Error Rate such as Backpropagation Neural Network (BPNN) and Support Vector Machines (SVM) with Radial Basis Function (RBF)..etc. [18,15].

In short, these analysis and classification methods achieved some accurate results, but these methods still have a lack of characterizing each human iris by a predefined analysis and classification parameters, the interclass similarity problem. Also, recognition performance of iris features still have many gaps to be improved, such as the intraclass variation, as well as the massive number of iris texture parameters [19]. Hence, several accurate iris recognition algorithms with multiscale analysis techniques in addition to a fast classifier are needed as a well-suited representation for iris verification.

Wavelet Transform (WT) is especially suitable for processing an iris image that satisfy these requirements. Since most details could be hardly represented by one function, they could be matched by various versions of the mother wavelet with various translations and dilations [20, 21]. Three problems will face wavelet transform in human iris verification system. First problem is the process of segmenting and normalizing the iris parts from each eye images without any eyelid and eyelash noise. This paper proposes Hough Transform and Daugman's rubber sheet model techniques in segmentation and normalization process [22]. Second, the feature extraction process are associated with the problems of interclass similarity, the down-sample process, and orientation invariant that make loss of some important extracted features from iris image. Thus, choosing the correct wavelet function at a determined level during feature extraction should help in solving this problem. Moreover, this paper proposes a Wavelet Neural Network (WNN) [23] technique as a local optimization method for iris verification to overcome these disadvantages and increase the intrinsic features. The third is the process of selecting the most effective and integrated parameters between DWT and WNN for optimal characterization to each human iris. In DWT the parameters are wavelet analysis function at effective analysis level. Also, WNN parameters are completely determined by wavelet activation function and learning rate value. Thus, choosing the parameters based on the correct wavelet function should affect the feasible domain of the wavelet activation function. Because of the lattice structure of WT Bank[24], a non-specific domain technique , independent from the specified problem, should serve in finding a general and global solution. Thus, a meta-heuristic based technique [25, 26] should be an effective searching strategy. Because of the slowness of GA and the population diversity problems, this paper introduces a distributed and meta-heuristic searching strategy based on GA[27, 28]. DGA is chosen as a global strategy searching technique to select the optimal integration between DWT and WNN parameters to characterize each human iris. DGA depends on interact among sub-population through the migration process, wherever each sub-population is addressed by a specific analysis level. By this paper, the migrated individuals are selected based on the wavelet entropy value.

This paper proposed an integrated hybrid model among DWT, WNN and distributed GA (new searching strategy based on GA) techniques for optimizing feature extraction and verification method for the human iris verification system. DWT technique analysis iris images to extract wavelet detail coefficients. According to a huge number of coefficients, a statistical model is represented by wavelet energy and entropy values [14]. Because of the problems of interclass similarity and intraclass variation, WNN technique will be used as a suitable classifier and increase the characterization features. DGA try to find the most effective DWT and WNN parameters for optimal characterization to each human iris. A testing stage examines the verification rate to the unseen iris. Moreover, the result will be concluded.

The rest of this paper is organized as; in Section 2, an abbreviation of Discrete Wavelet Transform (DWT), Wavelet Neural Network (WNN), and Genetic Algorithms (GA) are mentioned. Application of human iris verification using a proposed hybrid integrated system is described in Section 3. Section 4 declares the result of the proposed integration system. Moreover, a comparative study determine the verification rate between both strategies for iris verification systems (Searching for suitable integration between DWT and WNN parameters using standard GA and Distributed GA). Finally section 5 concludes the paper and give a recommendation for future work.

II. PRELIMINARIES

A. Wavelet Decomposition Analysis

Wavelets are basis functions that satisfy certain mathematical requirements. They are used to cut up data into different frequency components. Then, a study on the behavior for each component with a resolution matched to its scale[14]. The basic idea of wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the proposed function into different scale levels where each level is further decomposed with a resolution adapted to the level [29]. Thus, Wavelet function is characterized by a varying window size, wide for slow frequencies and narrow for fast ones. Furthermore, wavelet windows are adapted to the transients of each scale, regardless wavelets lack the requirement of stationary. For example, the signal x(t) is characterized by;

$$\left.\begin{aligned} x(t) = \sum_k s_{j,k}\phi_{j,k} + \sum_k d_{j,k}\psi_{j,k} + \sum_k d_{-1,k}\psi_{j,k} + .. + \sum_k d_{1,k}\psi_{j,k} \\ s_{j,k} = \int \phi_{j,k}\, x(t)dt \\ d_{j,k} = \int \psi_{j,k}\, x(t)dt \end{aligned}\right\} \quad (1)$$

Where $\psi_{j,k}(t)$ and $\phi_{j,k}(t)$ are the mother wavelet functions which analogous corresponding to sinusoidal basis function in Fourier Analysis. $\mathrm{s}_{\mathrm{j,k}}$ and $\mathrm{d}_{\mathrm{j,k}}$ are wavelet transform coefficient that we call them $\mathrm{w}_{\mathrm{j}}^{\mathrm{k}}$. Also $\mathrm{j} = 1,2,..\mathrm{J}$ is the number of multi-resolution levels (or scale) and k is the translation parameter. The Discrete wavelet transform, DWT, is selected to be dyadic scales and positions, i.e. the scales and shifts are based on power of two. Such analysis yielded from DWT is defined as;

$$DWT(j,k) = \mathrm{w}_{\mathrm{j}}^{\mathrm{k}} = \frac{1}{\sqrt{2^j}}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-2^j t}{2^j}\right) \qquad (2)$$

Where $\mathrm{w}_{\mathrm{j}}^{\mathrm{k}}$ is translated as the local remaining error between two successive signal approximations at scales j and $j+1$.

By implementing DWT on an image, it is actually decomposed into sub-bands and critically into sub-sampled. An efficient way for implementing this scheme is by passing the signal through a series of low pass and high pass filter pairs called as quadrature mirror filter as illustrated in Figure 2 [24]. 1-D level decomposition of DWT arises four sub-bands from separable applications of vertical and horizontal filters where L and H denote the 1-D low pass and high pass filter respectively. Low pass image LL corresponds to the coarse level coefficients, approximation image. On the other hand, three detail images HL, LH, and HH represent the finest scale as shown in Figure 2a. The LH channel contains image information of low horizontal frequency and high vertical frequency and so on. To obtain the next coarse level of wavelet decomposition, the sub-band LL is further decomposed and 2-D level decomposition is resulted, Figure 2b[29]. Repeatedly, this process is iterated until some final scale is reached, which is considered as one of the main goals in this paper.

By DWT analysis technique, the wavelet coefficients that are gathered from each sub-band (LL,HL, LH, and HH) are very huge to be certified as discrimination features. To overcome this problem, wavelet coefficients can be represented by statistical functions such as mean, median, standard deviation, energy and entropy [30].

Wavelet energy is the measure that keep the main characteristic of the wavelet coefficients and produce the same images with different translation, rotation and scale, having the same wavelet energy values[31, 32]. Wavelet energy values are measured by analyzed iris image to its wavelet sub-image coefficient (LLx, HLx, LHx, HHx) as defined in equations (3) [14] where $\mathrm{w}_{\mathrm{j}}^{\mathrm{k}}$ is the wavelet coefficients to sub-band j at k-level.

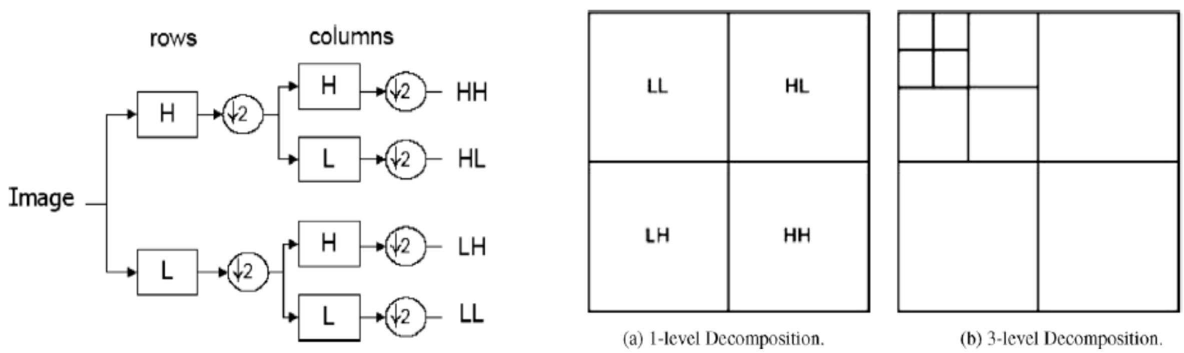


Fig. 2. A one-level wavelet analysis filter bank and Wavelet multi-level frequency decomposition

$$Ew^{(k)} = \frac{1}{\mathrm{J}}\sum_{\mathrm{j}=0}^{\mathrm{J}}(\mathrm{w}_{\mathrm{j}}^{\mathrm{k}})^2$$

Also, the energy at each resolution level $j = 1..J$ will be the energy of the detail signal

$$Ew_j = \sum_k \mathrm{w}_{\mathrm{j}}^{\mathrm{k}} \qquad (3)$$

wavelet entropy : wavelet entropy is an estimated measure based on the wavelet coefficients to provide quantitative information about the order/complexity of iris image [31]. Its values should be computed after analysis image to its wavelet sub-image coefficient (LLx, HLx, LHx, HHx). There are various wavelet entropy measures. The definition of norm entropy and sure entropy are defined by equations (4) respectively where w_i is the wavelet coefficients to sub-band x at k-level, Ɛ is a positive threshold value.

$$\left.\begin{array}{r} H_N(w)^{(k)} = \sum_{i=0}^{n} |w_i|^{\mathrm{p}} \quad for(1 \le p < 2) \\ |w_i| \le \mathcal{E} \;\; \rightarrow \; H_s(w)^{(k)} = \sum_{i=0}^{n} \min(w_i^2, \mathcal{E}^{\,2}) \end{array}\right\} \qquad (4)$$

B. Wavelet Neural Network

When the sigmoid activation function is used in training the neural network(NN), it can recognize any deterministic nonlinear process. But, NN suffer from a series of drawbacks. Random initial weights is generally associated with extended training times and NN may be trapped into local minima. Moreover, there is a shortage between the specific sigmoidal activation function and the admissible neural network architecture [33]. On the opposite, Wavelet neuron solve these problems. WNN is a feedforward neural network that gather both characteristics of neural network and wavelet decomposition. It is a generalization of the Redial based Neural Network(RBNN) by using wavelet as an activation function [34, 33]. RBNN is a bell shaped activation function that scale variable nonlinearity whereas WN does not consider symmetry condition in activation function. The reason for the application of WNN in case of such a problem as classification is that the feature extraction and representation properties of the wavelet transform are merged into the structure of the ANN to further extend the ability to approximate complicated patterns [35]. Moreover, WN is preserve in high compression ability and updating the function estimate from a new local measure, involves only a small subset of coefficients. The WN depends mainly on the bias that allows the sensitivity of the wavelet activation neuron to be adjusted. The architecture of WNN consists of three-layer structure with an input layer, a wavelet layer, and an output layer as shown in Figure 3.

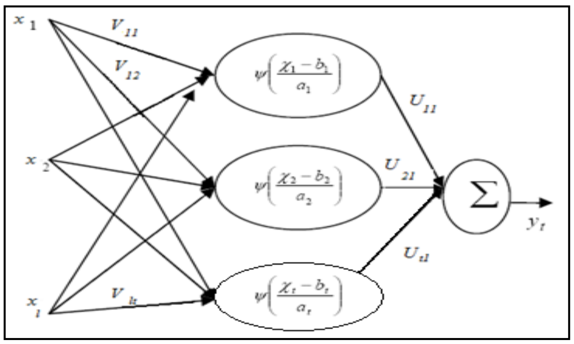
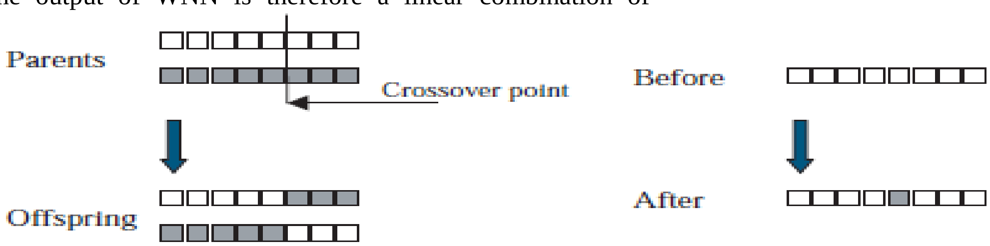


Fig. 3. The structure of the Wavelet Neural Network

In WNN, both the position and dilation of the wavelets as well as the weights are optimized. The basic neuron of a WNN is a multidimensional wavelet in which the dilation and translation coefficients are considered as neuron parameters. The output of WNN is therefore a linear combination of several multidimensional wavelets [34]. In this WNN model, the hidden neurons have wavelet activation functions ψ and have two parameter a_t, b_t which represent dilation and translation parameter of wavelet function and V is the weight connecting the input layer and hidden layer and U is the weight connecting the hidden layer and output layer.

C. Genetic Algorithms

Genetic Algorithm (GA), introduced by John Holland in 1975, is a computing search technique used in finding a solution in optimization problems. GA applies the principles of evolution found in nature to the problem of finding an optimal solution [36, 25]. GA generates successive populations of alternate solutions that are represented by a chromosome, i.e. a solution to the problem, until acceptable results are obtained. Each chromosome, individual solution, consists of number of binary code called genes. A fitness function assesses the quality of a solution in the evaluation step [28, 37]. The evolution from one generation to the next is performed using three operations: reproduction, crossover and mutation. Chromosomes are selected for reproduction by evaluating the fitness value. The fitter chromosomes have higher priority to be selected into the recombination pool using the roulette wheel or the tournament selection methods. Crossover selects genes from two parent chromosomes using randomly chosen crossover point and creates two new off springs as in Figure 4 (a). Mutation process changes chromosome randomly by altering a single bit as in Figure 4 (b).



(a) Crossover (b) Mutation

Fig. 4. Genetic algorithm operations

The evolutionary process operates many generations until termination condition satisfy. The termination condition is either reaching the maximum number of generations or a predefined fitness is achieved. Associated with the characteristics of exploitation and exploration search, GA can deal with large search spaces efficiently, and hence has less chance to get local optimal solution than other algorithms.

III. Human Iris Verification System Based on WNN

Human Iris Verification is considered as the most reliable and accurate biometric identification system [3, 38]. This paper presents an implementation for Human Iris Verification System using an integrated model among DWT in feature extraction phase, WNN in increasing the intrinsic features as well a fast classifier as local optimization method and Distributed GA (DGA) as an evolutionary searching strategy and a global optimization method. The proposed Human Iris verification system depends on several stages as depicted in Figure 5. First, segmenting and normalizing stage. The segmentation process isolates the iris part from an eye image without any eyelash and eyelid noise [4]. Then, normalizing the iris part process yields the corresponding texture based image [7, 22]. Second, extracting the intrinsic features for any iris texture image by discovering the optimal parameters between DWT and WNN. Since, iris texture is uniquely identifying each person based on its own characteristics; a stochastic searching strategy is needed to choose the optimal integration between DWT and WNN parameters. Unfortunately, conventional GA suffer from the premature convergence and the population diversity problems. In this paper, Distributed GA, the best large searching spaces strategy, is able to search for the optimal solution in adequate time[26, 37]. Finally, WNN verification rate, False Error rate, is measured for each human iris using the optimal parameters values.

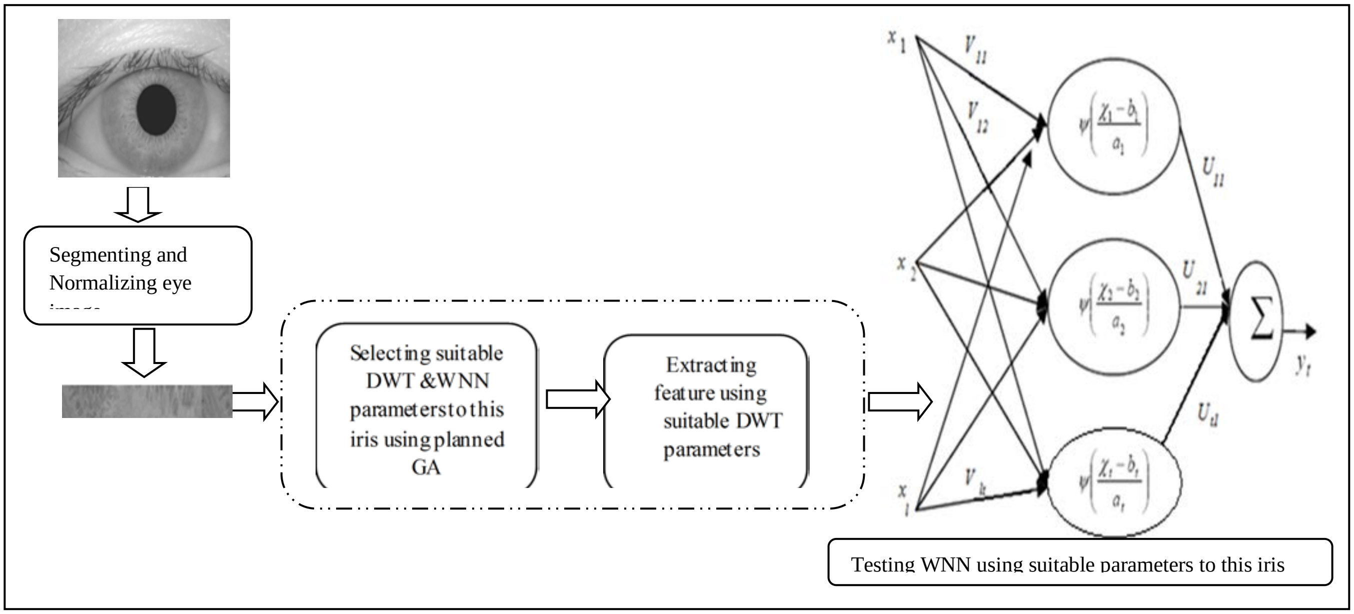


Fig. 5. Proposed Human Iris Verification System

A. Segmenting and Normalizing Stage

Each human eye image is segmented due to localizing the iris area. In this paper, Hough Transform [22] is used to localize the iris area from eye image, as shown in Figure 6. Units

Fig. 6. Example of iris normalization: (a) The iris localized area. (b) The normalized iris area

The Hough transform is a standard computer vision algorithm that can be used to determine the parameters of simple geometric objects, such as lines and circles, present in an image. An automatic segmentation algorithm based on the circular Hough transform can be employed to deduce the radius and center coordinates of the pupil and iris regions [3]. First, an edge map is generated by calculating the first derivatives of intensity values in an eye image and then thresholding the result. From the edge map, votes are cast in Hough space for the parameters of circles passing through each edge point. These parameters are the center coordinates x_c and y_c, and the radius r, which are able to define any circle according to the equation (5).

$$x^2_c + y^2_c - r^2 = 0 \tag{5}$$

Then, removing the eyelash from localized iris area is needed to get iris area pure from any noise as shown in ***Figure 1***. In this paper, *linear Hough transform* [7] remove eyelash from localized iris image by first fitting a line to the upper and lower eyelid. To detect the eyelids, approximating the upper and lower eyelids with parabolic arcs, which are represented by equation (6).

$$(-(x-h_j)\sin\theta_j + (y-k_j)\cos\theta_j) = a_j\left(\left(x-h_j\right)\cos\theta_j + \left(y-k_j\right)\sin\theta_j\right) \tag{6}$$

where a_j controls the curvature, (h_j, k_j) is the peak of the parabola and θ_j is the angle of rotation relative to the x-axis.

Normalizing the pure iris localized areas is needed to convert these area from different size to the same size as shown in Figure 6. In this paper, Daugman's rubber sheet model [22] is used to normalize iris for achieving more accurate verification system as in equation (7,8,9).

$$I(\, x(r,\theta)\,, y(r,\theta)\,) \longrightarrow I(r,\theta) \tag{7}$$

With respect to

$$x\,(r,\theta) = (1-r)x_p\,(\theta) + r\,x_1\,(\theta) \tag{8}$$

$$y\,(r,\theta) = (1-r)y_p\,(\theta) + r\,y_1\,(\theta) \tag{9}$$

where $I(x, y)$ is the iris region image, (x, y) are the original Cartesian coordinates, (r, θ) are the corresponding normalised polar coordinates, and x_p, y_p and x_1, y_1 are the coordinates of the pupil and iris boundaries along the θ direction.

B. Optimizing the Extracted Features using DGA

Because of the interclass similarity problem among iris textures, increasing the intrinsic feature for each human iris is persistent need. Moreover, as the result of the problem of intraclass variation, discovering the own iris texture parameters is also needed. Thus, a suitable integration between DWT and WNN parameters should serve in characterizing each human iris. Each iris texture should be characterized by its optimal wavelet analysis function at an optimal analysis level. Also, WA parameters with multiresolution analysis should be integrated with an optimal wavelet activation function with an effective learning rate value.

As a result a large feasible space of long string solutions is constructed. Thus a meta-heuristic search strategy is needed. Conventional GA (CGA) is an effective strategy for searching a large space although CGA schema is negatively affected by long defining chromosome. Wherever, schema with long chromosome length are more likely to be disrupted by single point crossover and fall in population diversity problem or premature convergence. Hence, a new searching strategy based on GA, distributed genetic algorithms, is introduced as an effective searching strategy that can deal with large space. The idea of DGA[28, 26] is to divide the large searching space into multiple small searching spaces. These sub-spaces interact together based mainly on the island or fusion models. In island model, Conventional GA is used as an effective searching strategy to search for the effective individuals in each sub-space. Then, a migration for optimal individuals among sub-spaces is run at a predefined number of generation. Since the synthesized wavelet composes much energy into low pass coefficients than the other does, then applying the proposed DWT to many levels should collect more energy in the same number of wavelet coefficients [32]. This paper implement DGA as a global optimization method to run on two consecutive processes. The first process is the division process of the large searching space based on the wavelet analysis level, multiresolution analysis. The individuals in each sub-space with maximum energy are chosen to migrate among the subpopulation at the migration step. This process tries to find the best individuals in each sub-space. Whereas, the second process search for the optimal solution from the best individuals resulting from the last one.

In the first process, Each sub-population is constructed based on the number of DWT analysis level. For each sub-population, the individual chromosome is represented as a combination of WNN parameters and DWT parameters at a predefined analysis level as depicted in Figure 7.

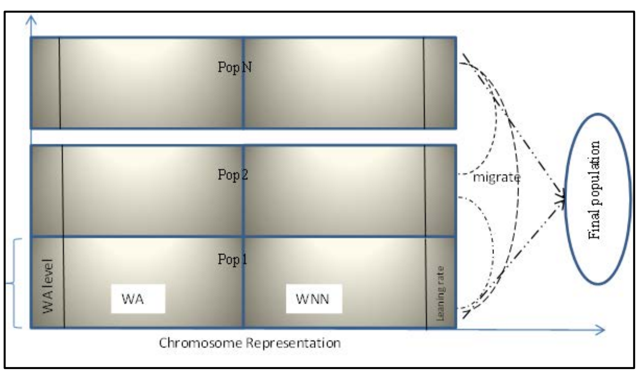


Fig. 7. The DGA level of sub-populations

Since each individual chromosome in the same sub-population have the same analysis level (N constant parameter value in each sub-population), GA schema length should be reduced. So, the searching space will be decreased as an effective way to standard GA in searching space.

a) Chromosome Representation

For each sub-population, GA chromosome is represented as a set of binary bits. These chromosomes should exactly contain six segments. The first segment of an individual chromosome represents the analysis level in DWT. Since different 8 wavelet analysis levels are ranged from N=3 To N=10, three bits are enough for representing this segment. The second segment of an individual chromosome represents the wavelet analysis function in DWT technique at Nth level. According to [3]five bits are enough for representing this segment (ranged from 00000 to 11111) however different 32 wavelet analysis function (db2, db3, db4, db5, db6, db7,db8, db9, db10, db12, db20, bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8,coif1, coif2, coif3, coif4, coif5, sym5) have the ability to analysis iris image and extracting wavelet detail features. The third segment of an individual represents the p-parameter value of the norm entropy , equation 3. In norm entropy, p values should be ranged in [1, 2) [14]. Sensitive p-parameter is considered to be 1/7, though p-parameter is represented by three bits for each individual chromosome (ranged from 000 to 111). Thus, the p-parameter gets one of the values: 1,1.142, 1.285, 1.426, 1.568, 1.71, 1.852 and 1.994. The forth segment of an individual represents Ɛ- parameter value of the sure entropy which is mentioned in equation 4. In sure entropy[14], the threshold Ɛ should be selected in [1, 8). Ɛ -parameter is represented by three bits for each individual chromosome. The Ɛ -parameter gets an integer value ranged from 1 to 8 .The fifth segment of an individual represents the wavelet activation function in WNN technique. Three bits are enough for representing this segment since different 8 wavelet activation function (Morlet,RASP1, RASP2, RASP3,POLYWOG1, POLYWOG2, POLYWOG3, POLYWOG4) [33] can be represented as a mathematical function. Finally the last segment of an individual represents the learning rate value in WNN technique. Learning rate value is selected in [0.1, 0.9) to decrease the time complexity for training WNN . Learning rate value is represented by three bits for each individual chromosome . Thus, the learning rate value gets one of the values: 0.2,0.3, 0.4, 0.5, 0.6 ,0.7, 0.8 and 0.9. Thus, each individual chromosome should be 20 binary bits in length. such an example, the encoded chromosome (01000001010011100000) is illustrated in Figure 8;

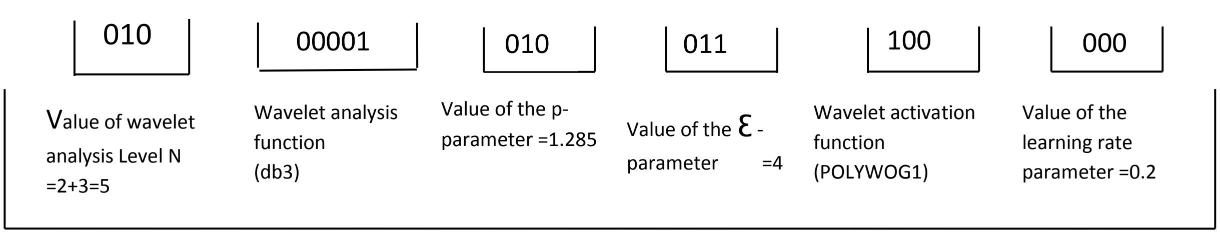


Fig. 8. a random individual chromosome in sub-population of N=5

The initial individual chromosome values in each sub-populations with size ζ_{g_0} of the first generation are initialized randomly, with different binary code. Each chromosome represents combination values among DWT and WNN parameters. The fitness value for each individual in each sub-population is evaluated by: extracting the wavelet energy and entropy values from all trained normalized iris images. These wavelet features is extracted from wavelet detail coefficients according to the corresponding wavelet analysis function and analysis level. These wavelet detail energy and entropy values are taken as input to WNN. The wavelet energy and entropy feature vector which is taken as input to WNN is shown in Figure 9 for n=1,…,N : n represent the level of wavelet decomposition.

b) Fitness Evaluation

Training the WNN with BP learning algorithm [34] compute the Mean Square Error (MSE) of the WNN at the last iteration as in equation 10. MSE is work as fitness function to each individual in each sub-population. The individual with the least MSE is the best individual in his sub-population. In the next generation, each individual is produced by reproduction, cross-over and mutation process over the individuals in the previous generation [27] using tournament selection strategy. As the result, each individual fitness function is evaluated. This process continues for a fixed number of generations. The best -so-far individual (the individual that has the best fitness overall generations) is designated as the best result for his sub-population.

$$\mathrm{MSE} = \frac{1}{\mathrm{Z_{MAX}}}\sum_{\mathrm{z=1}}^{\mathrm{Z_{MAX}}}(\mathrm{Y^z - D^z})^2 \qquad (10)$$

Where $\mathrm{z} = 1,\ldots\ldots \mathrm{Z_{MAX}}$, the number of input samples of WNN ; $\mathrm{Y^z}, \mathrm{D^z}$ represent the actual output of WNN and the expected output respectively for iris pattern z , D =(1|0). $\mathrm{D^z}$ =1 if the iris is the correct classified the human iris, and0 elsewhere.

c) Selection, Crossover, Mutation and Migration Process

Since N, number of resolution levels, sub-population should be constructed, communicated and evolved through $\mathrm{G_{max}}$ generations, all sub-populations are assumed with an equal size ζ_{g_0}. The first generation is randomly constructed with a constraint on similar individuals to be denied. For each chromosome individual, the WNN is trained with BP learning algorithm [34, 33], where the Mean Square Error (MSE), equation 10, represents each individual fitness value. In subsequent steps, each generation is evolved by constructing the pool mate with λ individuals from n^{th} sub-population $\mathrm{g^n(t)}$, using the tournament selection method. A single point crossover method is used with probability $\mathrm{p_c}$ to created two new individuals in the next generation. Also, a new individual is created based on the mutation process with varied probability $\mathrm{p_m}$ at each generation g[27].

$$\mathrm{p_m} = \mathrm{p_{m_0}} + \frac{3\mathrm{p_{m_0}} * g}{\mathrm{G_{max}}} \qquad (11)$$

$\mathrm{G_{max}}$ is the maximum number of generations and $\mathrm{p_{m_0}}$ is the initial mutation probability. The best so far individuals are selected as a new members in the next generation. For a fixed number of generations, the best individual so far is the most effective combination parameters between DWT and WNN methods which characterize the texture of human iris.

In the island model, the migration process from each sub-population $\mathrm{g^n(t)}$ execute a different evolutionary algorithm corresponding to a single decision variable. All the sub-population interact with themselves through the static hypercube migration process. The best chromosome in each sub-population migrate to another specific sub-population after each generation as depicted in Figure (7).The migration process depending on choosing the minimum number of wavelet coefficients that gain the same energy as the original iris texture. In other words the mother wavelet function that have wavelet energy with maximum values will be taken as migrate individual. Since the number of coefficients produced from the discrete wavelet decomposition is relatively equal or greater than the number of time samples of the original signal [39], then complexity of the signal approximation is chosen to be constant. The complexity of the signal is the ration between number of signal coefficients and the total number of signal samples $M = 2^N$.

$EHL^{(n)}$	$ELH^{(n)}$	$EHH^{(n)}$	$H_N(HL)^{(n)}$	$H_N(LH)^{(n)}$	$H_N(HH)^{(n)}$	$H_s(HL)^{(n)}$	$H_s(LH)^{(n)}$	$H_s(HH)^{(n)}$

Fig. 9. WNN input feature vector

Since wavelet representation of an iris image signal is resolved in only one wavelet resolution level, then the relative wavelet energy at any wavelet resolution level should be zero except at the wavelet resolution level that include the representative signal frequency[40,41]. To choose the migrated individual, a comparison among relative wavelet energy values, the wavelet entropy is used to make significate values. Thus the wavelet entropy (WE), equation 12,should converge to zero or diverge to very low value. The migrated individual is chosen with WE, as illustrated in Figure 10.

$$\left.\begin{aligned} WE &= -\sum \rho_j \log \rho_j \\ \rho_j &= \frac{Ew_j}{E_{tot}} \\ E_{tot} &= \sum_j \sum_k w_j^k \end{aligned}\right\} \qquad (12)$$

Function Genetic_ Algorithms(sub_pop, Fitness_f)

Input : Chromosome Set ($a_1, \dots, a_{\zeta_{g_0}}$), specific scale j, crossover probability p_c mutate probability p_m, the migration

Output: Best match chromosome for specified iris ($Best_{match}$)

1. At a specific scale j, construct ζ_{g_0}random individual, $g = 1$, tempEntropy=Max_val
2. While ($g \leq G_{max}$) do (Monitor. Enter(obj))
   a. Foreach (individual a_i in $\boldsymbol{\zeta_{g_0}}$)
      i. Extract w_j^k for each translation parameter. Compute the wavelet energy Ew_j (eq. 3)and wavelet norm and sure entropy with p and ε parameter (eq 4). Compute wavelet entropy WE(eq.12). Calculate fitness for each individual , eq. 10, inside the subpopulation in the corresponding client.
      ii. If ($f(a_i) > f(Best_{match})$)
         - $Best_{match}$=a_i
      iii. If($WE_i < tempEntropy$)
         - $tempEntropy = WE_i$
         - $MigratElement = i$
   b. MigrateList.add($a_{MigratElement}$)
   c. By tournament selection, construct pool mate with λ individuals, then combine two individuals with probability p_c and mutate individuals with probability p_m , then change p_m (Eq. 11) .
   d. Replace the worst individuals by the fittest in the current generation
   e. If ($g\%migrate_{Parm}! = 0$)
      i. Monitor. Pulse(obj)
      ii. Else
      - Monitor. Wait (obj)
      - replace worst chromosomes by MigrateList from another island.
   f. $g + +$ (Monitor. Exit(obj))
3. Return $Best_{match}$

Fig. 10. DGA sub-space

In the last stage, the WNN input layer represents wavelet energy and entropy values feature vector to WNN. The output layer represents the verified human iris. The middle layer determined the ability to learn the human iris recognition. The result in the output layer is either match (0) or unmatched (1).

IV. Simulated Results

This section summarizes the results of using the proposed hybrid integrated system among DWT as feature extraction technique, WNN as classifier technique and Distributed GA as a searching strategy to select the optimal characterization for each human iris texture. This paper uses nine person eye images from CASIA-IrisV3-Interval eyes database[42]. each person has twenty images of his right eye, ten for train stage and another ten for test stage.

In ***Segmenting and Normalizing Stage***, For the CASIA database, values of the iris radius range from 90 to 150 pixels, while the pupil radius ranges from 28 to 75 pixels [22]. In order to make the circle detection process more efficient and accurate, the Hough transform for the iris/sclera boundary was performed first, then the Hough transform for the iris/pupil boundary was performed within the iris region, instead of the whole eye region, since the pupil is always within the iris region.

After this process was complete, six parameters are stored, the radius, and x and y center coordinates for both circles.

In ***feature extraction and optimization method***, Distributed GA with two levels searching strategy is used to select the most effective integration between DWT and WNN parameters to each person. The parameters GA, DWT and WNN for each individual in the integrated system are shown in Table1.

TABLE I. GA, DWT and WNN Parameter for Selecting the Most Effective Parameters to Each Human Iris

GA parameters (First and Second searching Level)	
Sub- Population numbers	8
Population Size	200
Number of generation	100
Number of individual in each tournament selection	5
Reproduction percentage	14 % from population size
Crossover percentage	85.5% from population size
Mutation percentage	0.5% from population size
Number of tries trails	10
DWT analysis parameters	
Number of best analysis level	5 level
WNN architecture and training parameters	
The number of layers	3
The number of neuron on the layers	Input:21 Hidden:42 Output:1
The initial weights and biases	Random values
Learning rule	Back-Propagation
Number of epochs	500

As a result from the integrated system, Table2 shows the most effective integration between DWT and WNN parameters to each human iris from different (32 wavelet analysis function , 8 p-parameter ,8 Ɛ-parameter, 8 wavelet activation function and 8 Learning rate values) all at analysis level N=5 as a result from Distributed GA.

To evaluate our proposed system, a comparative study between two strategies for iris verification systems:

1) Searching for suitable integration between DWT and WNN parameters using standard GA (DWT+WNN+GA).

2) Searching for suitable integration between DWT and WNN parameters using planned GA (DWT+WNN+planned GA).

Figure 11 represent the verification rate to each testing human iris data verification rate ranged from 100% to 98% to our proposed system. Since our proposed system has training verification rate 100% to all training data. Figure 11 concluded that our proposed system has the highest verification rate.

TABLE II. THE RESULT OF DISTRIBUTED GA SEARCHING PARAMETERS

Person number	Suitable wavelet analysis function	Suitable p-norm parameter value	Suitable Ɛ-sure parameter value	Suitable wavelet activation function	Suitable Learning rate value
P1	bior 5.5	1	1	POLYWOG3	0.2
P2	coif1	1.994	6	Morlet	0.5
P3	db4	1.142	4	RASP2	0.9
P4	coif3	1.71	2	POLYWOG3	0.9
P5	bior 3.9	1	5	RASP3	0.6
P6	db20	1.285	3	POLYWOG3	0.6
P7	sym5	1.994	1	POLYWOG2	0.4
P8	db9	1.42	6	Morlet	0.3
P9	db2	1	8	RASP1	0.2

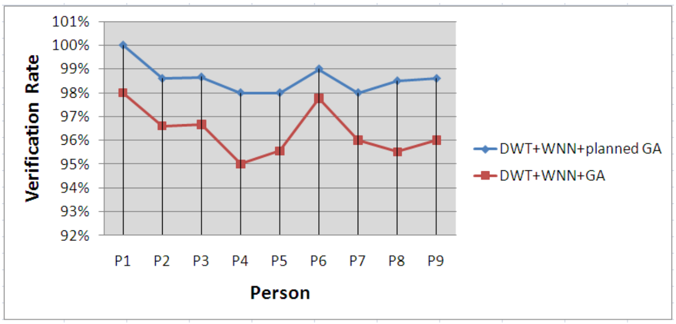


Fig. 11. Comparative Study between two version of the proposed hybrid integration system using conventional GA and distributed GA in Human Iris Verification Systems

Thus the performance of WNN is evaluated based on classification accuracy;

$$Classifcation\ Accuracy = \frac{\{correct\ clasifed\ pattern\}}{\{Total\ Patterns\}} = 98.5$$

V. CONCLUSIONS AND FUTURE WORK

Human Iris verification plays an important role in the daily life especially for security purposes. Human iris verification system suffers from several drawbacks, such as the interclass similarity and intraclass variations. Moreover some additional difficulties arose during learning process such as discovering the optimal iris texture and increasing the intrinsic features for each iris image. This paper tries to overcome these problems by optimizing and integrating model of DWT and WNN. The problems appeared by DWT, the down sampling process as well as the optimal wavelet analysis function associated with the most effective analysis level, are solved based on the global optimization method of Distributed GA. Besides WNN, a good and fast classifier, increases the intrinsic feature and works as a local optimization method. Also, WNN overcome the problem of lost information during DWT down sampling process. Because of the large searching space that represents the optimal DWT and WNN parameters, Distributed GA , new searching strategy based on GA, is used to search for an optimal wavelet analysis function at the most effective analysis level. Moreover, Distributed GA search for the optimal WNN activation function and the learning rate value. The benefit of Distributed GA in dealing with large searching space is to avoid the problems of premature convergence and population diversity. By this work, the integration between DWT and WNN optimal parameters were able to introduce a new verification system that applied on CASIA database. The results demonstrate that this integration achieve good solution. Hence, a comparative study of human iris verification systems is appeared. The conclusion finds that our proposed system has high verification rate.

Unfortunately, Iris recognition system still undesirably increase recall rate so, it is in a need of more and more work. In future work, a new hybrid data fusion classification system should achieve better recognition in the digital iris image. The proposed system as any classification system based on the quality of the set of features characterizes the pattern and the efficiency of the classifier. A data fusion system based on two methods for texture analysis and constructing the set of features characterizes iris texture image is proposed. The first method is a statistical method to analyze the spatial distribution of gray values using co-occurrence matrix. The second method is a filtering method to analyze the frequency content of the iris image using contour-let transform. The data fusion system combines the extracted features, though an augmented features database is constructed.

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