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Soft Computing: Two-Step Feature Extraction-Based Biometric Authentication System

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Abstract: *There are many biometric authentication systems that have used different human traits either physiological or behavioural which are liable to forgery. Thus, the human tongue promises to deliver a level of uniqueness that other biometrics cannot match because it is immune to forgery. However, literature has revealed that a single feature extraction technique was not sufficient for effective and efficient treatment of biometrics because of lapses imposed by individual technique. This paperpresents the development of a tongue recognition system using Gabor filter and particle swarm optimization. One hundred and twenty tongue images of human tongues of different individuals, six tongue images with different expressions were captured each per person with a digital camera. The tongue images were pre-processed through extraction of region of interest and normalization usingbinary mask and histogram equalization; Gabor filter was used for feature extraction and particle swarm optimization (PSO) was used to select salient features.Some samples tongue images were matched with the stored extracted tongue images using Euclidean distance classifier. The results show that at threshold value of 0.50, G-PSO has a sensitivity, specificity and accuracy rate of 100.00%, 94.44% and 98.08% respectively compared to Gabor which has 94.12%, 88.89% and 92.31% respectively and PSO which has 97.06%, 88.89% and 94.23% respectively.*

Keywords: *Gabor filter, PSO, threshold, Euclidean distance, G-PSO.*

I. Introduction

Establishing the identity of a person is becoming critical in our vastly interconnected society. Questions like “Is he really who he claims to be?”, “Is this individual authorized to make use of this facility?” are routinely being posed in a variety of scenarios ranging from issuing a driver’s licence to gaining entry into a country. [5]. Thus, impersonation is a very big security threat to biometric systems. This is performed by the use of artifacts or by finding an existing person with a similar biometric data and then fraudulently assuming that identity to spoof a verification check. However, a biometric-based verification system works properly only if the verifier system can guarantee that the biometrics data came from the legitimate person at the time of enrollment so that during verification when a user claims an identity it is validated by comparing the stored biometric data against their presented biometric features [2]. It is therefore important to examine the accuracy of biometric tools when subjected to such attacks. If biometric systems are to prevent these attacks, the systems need to be made complex for impersonations or impostors by combining more than one biometric data or use more than one classifiers for verification and authentication purposes.

Although biometric systems have used different human traits like fingerprint, tongue, iris, palm-print, ear, etc, for authentication and recognition. But all these authentication systems have some flaws at some extent and as a result they can be forged by some fraudster by fooling the authentication system, and thus claiming to be an authorized user when they are not. [1] [2]. This had prompted the researchers to employ tongue trait for biometric authentication because of its uniqueness. Although tongue recognition has received considerably less attention than many alternative biometrics, but it was discovered to be a unique organ which reside inside the mouth, proven to be difficult to forge or affected by external environment and does not react to factors such as mood, health, and/or clothing [3].

A. The Structure Of Tongue

The tongue is a muscular organ on the floor of the mouth of most vertebrates that manipulates food for chewing. It is the primary organ of taste because most of its upper surface is covered with taste buds. The tongue is very sensitive and kept moist by saliva [6]. The tongue is covered with moist, pink tissue called mucosa. Tiny bumps called papillae give the tongue its rough texture as shown in Figure 1. Thousands of taste buds cover the surfaces of the papillae [7]. In some animals (for example, frogs) it is elongated and adapted to capturing insect prey. The tongues of certain reptiles function primarily as sensory organs, whereas cats and some other mammals use their tongues as instruments for grooming and cleaning. In mammals the tongue aids in creating negative pressure within the oral cavity that enables sucking. In humans the front tips and margins of the tongue usually touch the teeth which allows the tongue to make speech sounds.

The tongue is a unique organ in that it can be stuck out of mouth for inspection, and yet it is otherwise well protected in the mouth and is difficult to forge. The tongue also presents both geometric shape information and physiological texture information which are potentially useful in identity verification applications.

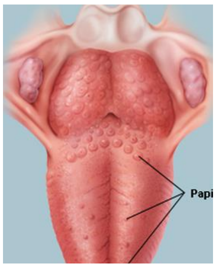

Figure 1: The dorsal view of the human tongue

II. RELATED WORK

Many researchers have performed experiments on identification system using tongue traits. For instance, the authors in [11] presented a newly developed 3D tongue image database, they provide both tongue shape and tongue textures. That was the first attempt at making a 3D tongue image database available for the research, with the ultimate goal of fostering the research on tongue biometrics. The new database can be a useful resource for tongue recognition for authentication and identification systems. While the researchers in [12] developed tongue recognition system for identification by using scale invariant feature transform (SIFT) feature extraction algorithm on the above developed database. The authors in [10] concatenate the face and palmprint using XOR, AND and OR gate with thehelp of Particle Swarm Optimization (PSO) algorithm. In recognition, the concatenated feature is matched through distance matching and distance score provides recognition identity of a person. The proposed technique is implemented with the help of evaluation metrics such as false acceptance rate, false rejection rate and accuracy. Finally the comparative analysis for the proposed fusion technique results 40% better accuracy, when compared with the existing techniques.The researchers in [7] proposed a computerized tongue diagnosis where Bayesian Network classifier based on chromatic and textural measurements to classify healthy and abnormal tongues (13 diseases) from a group of four hundred and fifty-five patients. The correct classification rate was estimated as 75.8%. Gabor Wavelet Opponent Colour Features (GWOCF) was developed by [13] to analyze tongue images in order to perform a tongue diagnosis in TCM. In particular, they employed colour information to pre-classify the known texture image before extracting GWOCF to achieve 89% recognition rate using patient's tongue images captured in Guangzhou Traditional Chinese Medicine Hospital. The authors in [14] computed the entropy and energy functions to represent the texture features, and employed a k-Means algorithm to select the clusters and finally used 3-D visualization to classify eleven normal tongue images and eight tongue images from patients with gastro cancer. The author concluded that color and texture features are sensitive to abnormal tongues.

The researchers [9] employed Particle Swarm Optimization (PSO) algorithm and applied in feedforward neural network to enhance the learning process in terms of convergence rate and classification accuracy.Two experiments have been conducted; Particle Swarm Optimization Feed-forward Neural Network (PSONN) and Genetic Algorithm Backpropagation Neural Network (GANN). The results show that PSONN give promising results in terms of convergence rate and classification accuracy compared to GANN. Authors in [15] designed a Computerized Tongue Examination System (CTES) to automate the diagnostic of tongue images based on chromatic and spatial textural properties. In particular, colours of substance and coating, thickness of coating and the detection of grimy coating have been measured.Indeed, textural features including the angular second moment (ASM), contrast, correlation, variance and entropy were used to determine the grimy coating of the tongue. The k-NN algorithm successfully classified 86% of the tongue images. The authors concluded that there is areal potential for computerized tongue diagnosis. The authors in [17] proposed a modelling step based on an hybrid algorithm, that includes Particle Swarm Optimization and Genetic Algorithm, is proposed to combine two biometric modalities at the score level. This optimization technique developed found the optimum weights associated to the modalities being fused. An analysis of the results is carried out on the basis of comparing the EER accuracies and ROC curves of the fusion techniques. Likewise the researchers in [18] The algorithm is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transforms (DCT) and the discrete wavelet transform (DWT). The proposedPSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well defined discrimination criterion.

Evolution is driven by a fitness function defined in terms of maximizing the class separation (scatter index). The

classifier performance and the length of selected feature vector are considered for performance evaluation using the
ORL face database. Experimental results show that the PSO-based feature selection algorithm was found to generate
excellent recognition results with the minimal set of selected feature. Related works can be found in [16], {19]

III. GABOR FILTER

The functionality of the Gabor filters are very near to the neurons of the visual system and also it serves as a solution for mutual information maximization problem. Maximum information from local image regions can be extracted using Gabor receptive field. For face recognition applications, the number of Gabor filters used to convolve face images varies with applications, but usually 40 filters (5 scales and 8 orientations) are used.

A Gabor filter is a linear filter used for texture analysis, this means that it analysis the point or region of analysis of an image to check if there are any specific frequency content in specific directions in a localized region. A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope.

The one dimension (1-D) Gabor filter was first defined by Gabor and was later extended to 2-D by Daugman [5]. The Gabor filter is extensively used in texture analysis since it decomposes an image into components corresponding to different scales and orientations. The two-dimensional (2D) Gabor is able to capture visual properties such as spatial localization, orientation selectivity, and spatial frequency. Thus, Gabor filter is well-adapted for image processing applications; especially texture analysis. The 2D Gabor filter is the product of a 2D Gaussian and a complex exponential function.

The general form of the real part of a 2-D Gabor function is defined as follows:

$$G(x, y, \sigma_x, \sigma_y, f, \theta) = \exp\left[-\frac{1}{2}\left(\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right)\right]\cos(2\pi f x')(1)$$

$$x' = \text{x}\cos(\theta) + ysin(\theta) \qquad (2)$$

$$y' = \text{y}\cos(\theta) - xsin(\theta)(3)$$

Where σ_x and $\sigma_y\sigma_y$are respectively the standard deviations of the Gaussian envelope along the *x* and *y* axes respectively. The parameters f and θ are respectively the central frequency andthe rotation of the Gabor filter. Then, to obtain the Gabor-filtered image *f* (*x*,*y*) of a given input image *I*(*x*,*y*) the 2-D convolution operation (*) is performed as follows

$$f(x, y) = G(x, y, \sigma_x, \sigma_y, f, \theta) * I(x, y) \qquad (4)$$

The feature extractiontechnique proposed in this article uses 2D Gabor filter banks and produces robust 3D face feature vectors. A supervised classifier, using minimum average distances, is developed for these vectors. The recognition process is completed by a threshold-based face verification method, also provided. A highfacial recognition rate is obtained using this technique.

IV. PARTICLE SWARM OPTIMIZATION

PSO proposed by Dr.Eberhart and Dr. Kennedy in 1995 is a computational paradigm based on the idea of collaborative behavior and swarming in biological populations inspired by the social behavior of bird flocking or fish schooling. Recently PSO has been applied as an effective optimizer in many domains such as training artificial neural networks, linear constrained function optimization, wireless network optimization, data clustering, and many other areas where GA can be applied. [8].

When PSO is used to solve an optimization problem, a swarm of computational elements, called particles, is used to explore the solution space for an optimum solution. Each particle represents a candidate solution and is identified with specific coordinates in the D-dimensional search space. The position of the i -th particle is represented as $X_i = (x_{i1}, x_{i2}, \ldots\ldots x_{iD})$. The velocity of a particle (rate of the position change between the current position and the next) is denoted as $V_i = (v_{i1}, v_{i2}, \ldots\ldots v_{iD})$. The fitness function is evaluated for each particle in the swarm and is compared to the fitness of the best previous result for that particle and to the fitness of the best particle among all particles in the swarm. After finding the two best values, the particles evolve by updating their velocities and positions according to the following equations:

$$V_i(t+1) = \omega \times V_i(t) + c_1 \times \text{Rand}(\ ) \times [pBest - X_i(t)] + c_2 \times \text{Rand}(\ ) \times [\text{gBest} - \text{Xi(t)}] \qquad (5)$$

$$X_i\,(t+1) = x_i\,(t) + V_i(t+1)\ \ x_i(t+1) = x_i(t) + V_i(t+1)(6)$$

Vi(t) is the agent's velocity,$x_i(t)$ is the current position of the agent, *w* is the inertia weight and Rand() is a random number between 0 and 1. C_1C_1andC_2C_2 are the learning factors and usually $C_1 = C_2 = 2$. The previous best position of particle i is denoted by pBest and the previous global best is denoted by gBest. In equation 5 the first component represents the inertia of pervious velocity. The inertia weight ω, is a factor used to control the balance of the search algorithm between exploration and exploitation; the second component is the "cognitive" component representing

the private experience of the particle itself; the third component is the "social" component, representing the cooperation among the particles. The recursive steps will go on until we reach the termination condition (maximum number of iterations K).
By simulating individual learning and social cultural transmission PSO attains both simplicity and efficiency (speed of convergence). Some of the advantages of PSO are, it has performed well on a variety of benchmark problems, such as, Schaffer function and global minimum. Also in a wide range of applications such as, minimizing the weight of a tension spring (engineering optimization problem) and neural network optimization. But it does not accurately reflect the accurate human belief system and performance is problem dependent.

V. METHODOLOGY

The block diagram of the tongue recognition system is shown in figure 2.

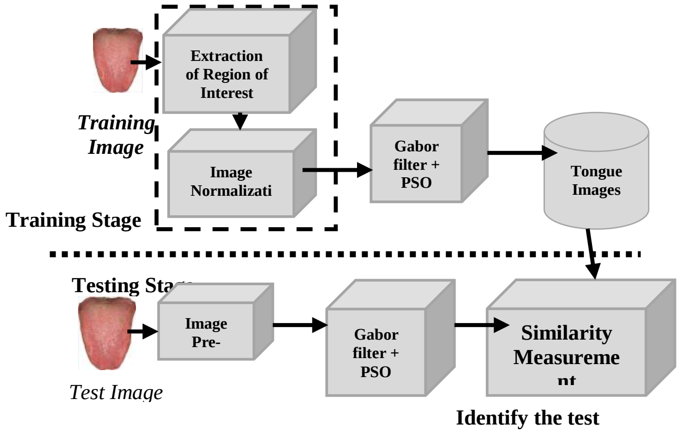

Figure 2: Block diagram of the proposed system.

Captured Images
The images used for this experiment was acquired using a digital camera of Sony - Alpha a7Full-Frame Mirrorless Camera with 28-70mm Lens mounted on tripod stand. A total of 120 images were used in the course of the experiment. Images were acquired in Joint photographic Expert Group (JPEG) formats. Samples are shown in figure 3.

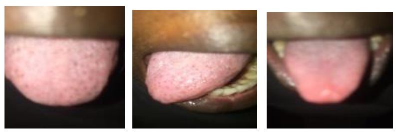

Figure 3: Sample of tongue images

Image Pre-processing
The image pre-processing step comprises of (i) operations like image scaling, image brightness and contrast adjustment, filtering, cropping and other image enhancement operations by ***histogram equalizer***, and (ii) extraction of region of interest (ROI) and normalizing of tongue vectors by calculating the average tongue vector and subtracting average tongue from each tongue vector by ***binary mask***. This was done to remove noise and other unwanted element from the tongue images. Sample output is shown in appendix A (ii and iii).

Texture Feature Extraction
After the extraction of interest from the tongue images and the normalization of the images, Gabor filters was then used for feature extraction. Gabor filters is used to obtain some feature vectors which provide optimal characterizations of the visual content of images.

Features Selection
Particle Swarm Optimization (PSO) was used to perform the selection of some unique features from the tongues features extracted by Gabor filter. PSO will select a subset of the most discriminating features from the whole feature set for building robust learning models.

Images Matching
It is used to compare the extracted biometric raw data to one or more previously stored biometric templates. The module therefore determines the degree of similarity (or of divergence) between two biometric vectors.The extracted features of the tongue are compared with the tongue images in the database by Euclidean distance.Sample output is shown in appendix A (iv).

VI. DISCUSSION OF RESULTS

An interactive Graphic User Interface (GUI) was developed, as shown in figure 4. The implementation tool used was MATLAB R2012a version on Windows 7 Ultimate 32-bit operating system, Intel®Pentium® CPU B960@2.20GHZ Central Processing Unit, 4GB Random Access Memory and 500GB hard disk drive.

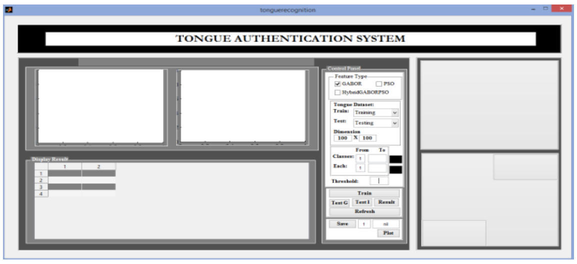

Figure 4: Tongue Identification System GUI

The experiment was performed with fifty-two images to test the tongue recognition system meaning two images per seventeen subjects plus six images per the remaining three untrained subjects that are not in the database. The result as shown in Table 1 presented values of sensitivity, specificity and recognition accuracy generated by Gabor, PSO and G-PSO at threshold value of 0.50.

The recognition accuracy with G-PSO generated 98.08% compared with 94.23% produced by PSO and 92.31% gotten by Gabor at threshold value of 0.50. The sensitivity with G-PSO produced 100.00% compared with 97.06% produced by PSO and 94.12% gotten by Gabor at threshold values of 0.50. The specificity with G-PSO made 94.44% compared with 88.89% generated by PSO and 88.89% gotten by Gabor at threshold values of 0.50. It was deduced that G-PSO produced the highest values for recognition accuracy, specificity and sensitivity.

VII. CONCLUSION

This research work evaluated the intrinsic features of Gabor, PSO and a combined form of Gabor and PSO algorithms on tongue recognition system in other to determine their effectiveness on the developed system. The tongue recognition system was preprocessed and its feature was extracted and selected by using Gabor and PSO respectively. Euclidean distance algorithm was employed for classification.

Sixty-eight images were trained and fifty-two images were tested at threshold value 0.5. The experimental results obtained revealed better recognition accuracies in respect of G-PSO over Gabor and PSO. Also, G-PSO recorded 100.00% sensitivity compared with 94.12% generated by Gabor and 97.06% produced by PSO at threshold value of 0.50. In view of this, the combined form of Gabor and PSO algorithm-based system would produce a more efficient and accurate tongue-ailment detection machine than Gabor and PSO algorithm-based tongue recognition system.

Table 1: Table showing results of the algorithms at threshold 0.50

Algorithms	TP	FP	FN	TN	SEN %	SPEC &	ACC %
Gabor	32	2	2	16	94.12	88.9	92.31
PSO	33	2	1	16	97.06	88.9	94.23
G-PSO	34	1	0	17	100.00	94.4	98.08

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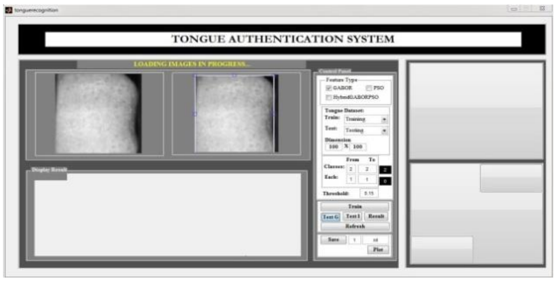
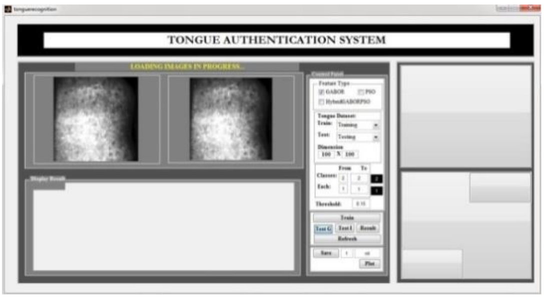
Appendix A

(i) GUI before extraction of ROI



(ii) GUI after extraction of ROI



(iii) GUI after normalization of a tongue image

(iv) GUI showing matching of dataset with G-PSO