Performance Evaluation of Some Selected Feature Extraction Algorithms in Ear Biometrics

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Abstract: ***It has been suggested by the researchers that the structural shape, size and features of the ear are unique for each person and invariant with age, which makes ear a better biometric trait; however, a major problem in ear recognition is extraction of the specific key points. This research work investigates four key feature extraction techniques: Principal Component Analysis (PCA), Speeded Up Robust Features (SURF), Geometric feature extraction and Gabor filter based feature extraction techniques in terms of performance issues given by False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR) and Recognition Accuracy in order to determine the best approach (or approaches) that can best maximize security features of Ear Biometrics Systems. The results suggest the potential power of ear biometrics and demonstrate the effectiveness and efficiency of these feature extraction techniques, confirming that PCA and Gabor feature extraction algorithms are indeed efficient and strong techniques for normal pose of the ear, obtaining Recognition Accuracies of 98.95% and 97.93% respectively. SURF is the most efficient in the presence of occlusion with tiny earring obtaining a GAR of 81.82%. Gabor wavelet and SURF are invariant to rotation.***

Keywords: Ear biometrics, Gabor wavelet, Occlusion, Principal Component Analysis (PCA)

1. Introduction

The new feature in biometrics is human ear which is becoming popular because if offers several advantages over other biometric technologies including: rich and stable features, ear is unaffected by mood or health, the image acquisition of human ear is very easy as it can be captured from a distance without the cooperation of the individual. The potential for using the ear's appearance as a means of personal identification was recognized and advocated as early as 1890 by the French criminologist Alphonse Bertillon (Bertilon *et al.,* 1980).

The limitations of other biometric modes of authentication (fingerprints, face, iris, hand geometry, voice, or gait) such as expression changes, changing lightning, makeup or eye glasses, have encouraged the use of ear biometric systems to establish human identity. However, ear recognition system still has many problems. The major problems in ear recognition are attitude problem, the noise on the ear image and the extraction of the specific key points; of these problems, feature extraction is the most critical (Wilson, 2004). It is the most important and main part of digital image processing and severely affects the recognition accuracy. This research work evaluates four selected key feature extraction algorithms using the biometric performance metrics in order to determine the performance of each algorithm.

The study of Ear began with the work of Iannarelli (1989)where ear was claimed to be unique to each individual. The Ear was further classified by dividing it into seven parts as shown in Fig. 1. Medical reports have shown that the variation over time in ear is most noticeable during the period from four months to eight years old and over 70 years old (Li *et al.*, 2015). Due to the ear's stability and predictable changes, ear features are potentially a promising biometric for use in a human identification (Bhanu*et al.*, 2007).

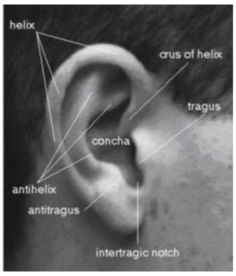

Figure 1: Anatomy of an ear (Dasari, 2007).

2. Methodology

The system was designed using MATLAB R2013a programming Environment. The choice of the design environment is based on the availability of image processing applications.

2.1 Data Collection

Over 500 non public ear images were collected using Tecno P9 Camera in the same lightening conditions with no illumination changes. The images were carefully taken from the right side of the face to preserve the outer ear shape with a distance of 15-20 cm (Dasari, 2007) between the face and the camera. These images are used for training the automatic ear detector and for recognition.

2.2 The Proposed Ear Recognition System

The proposed Ear Recognition System is divided into five major steps- Image acquisition, Edge detection and normalization, Feature extraction, Feature selection and Ear recognition. Fig. 2 shows a proposed flow diagram for the ear recognition system.

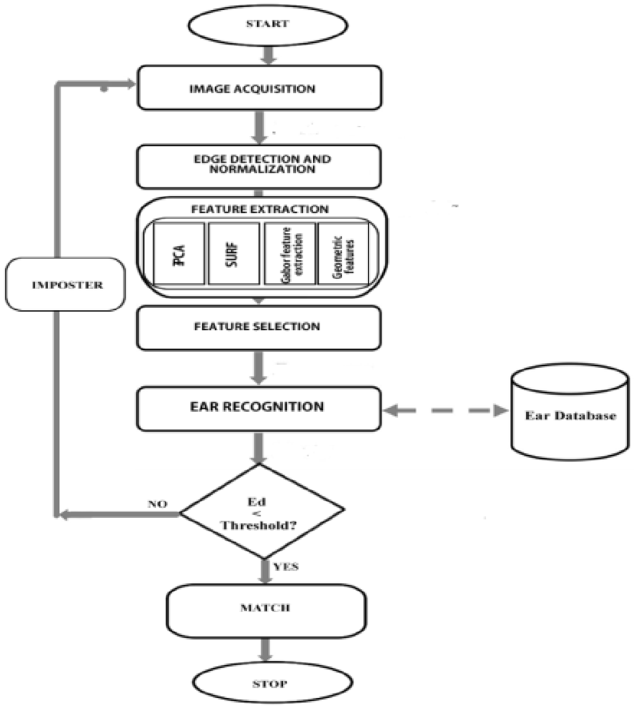

Figure 2: Flowchart of the proposed Ear Recognition System.

2.3 Image Acquisition

The side image is acquired from a system's web camera using the webcam object in Matlab. The webcam object connects to the camera establishing exclusive access and starts streaming. The image is then previewed and acquired using the Matlab snapshot function.

2.4 Edge Detection and Normalization

The Region of Interest (ROI) in this research work is the Ear; which is detected by trained a cascade detector in Matlab. After the ROI selection, the image is converted to grayscale and the edge detection is done using the canny edge detector (Canny, 1986). Median filter is used to remove noises and Standard deviation computation is made to enhance the dimension of the output image so that it helps to detect edges clearly. Normalization is done by considering the Ear image estimated mean (M) and variance (v). The input image I (x, y) is normalized by using the equations:

$_i(x, y) = M_0 +$; if $I(x, y) \geq M$ (1)

$N_i(x, y) = M_0$ -; otherwise (2)

2.5 Feature Extraction

After completion of ROI selection, enhancement and normalization operations, the images are ready for feature extraction. The Concha is taken as the local feature and Outer Helix is taken as the global part of ear image.In this proposed approach, four key feature extraction techniques are used. The four feature extraction algorithms are selected based on their rank-1 performance as shown from the work of Anika*et al.*(2012). The four feature extraction algorithms considered in this research work are:

1) Principal Component Analysis (PCA)
2) Speeded Up Robust Feature (SURF) Transform
3) Gabor wavelet based feature extraction
4) Geometric features

2.5.1 Principal Component Analysis (PCA)

The 'principal components' are obtained by the Eigen decomposition of the covariance matrix of the ear data, the dimensionality is then reduced by finding a linear subspace of the original feature space on to which the ear data is projected such that the projection error is minimized. Each image's pixels are taken row by row from top to bottom and converted to a row vector containing the gray scale or intensity values of that image. These row vectors are then concatenated in a single matrix so that each row in that matrix corresponds to an image. This process is done to training images as well as test images, keeping them in two separate matrices.

The covariance matrix is then calculated for the training images where each row represents an image (observation) and each column represent a pixel position (variable). Covariance is the measure of how much two variables vary together which is calculated using the following formula:

$$cov(x_i,x_j)= E((x_i - \mu_i)(x_j - \mu_j)) \text{ For i and j} = 1,2,....,n \quad (3)$$

where E is the mathematical expectation and $\mu_i = Ex_i$, and x is the training images matrix. If the size of x is (m x n), where m is the number of images (rows) and n is the number of pixels per image (columns), then the resulting covariance matrix (C) will be of size (n x n). If the covariance matrix (C) satisfies the relation $Ce_i = \lambda_i e_i$; where $\lambda_i$and e_i for i=1,2…,n are the corresponding eigenvectors and eigenvalues respectively, then matrix A from the eigenvectors sorted by decreasing eigenvalues is constructed.

2.5.2 Speeded Up Robust Feature Transform Features (SURF)

There are two important steps involved in extracting SURF features from an Ear image. These are finding key-points and computation of their respective descriptor vectors.

SURF makes use of hessian matrix for key-point detection. For a given point P(x; y) in an image I, the hessian matrix is defined as:

$$H(P,\sigma) = (4)$$

Where $Lxx(P,\sigma)$, $Lxy(P,\sigma)$, $Lyz(P,\sigma)$ and $Lyy(P,\sigma)$ are the convolution of the Gaussian second order derivatives $g(\sigma)$, $g(\sigma)$,$g(\sigma)$, and $g(\sigma)$, with the image I at point P respectively.

In order to generate the descriptor vector of a key-point, a circular region is considered around each detected key-points and Haar wavelet responses dx and dy in horizontal and vertical directions are computed.

2.5.3 Gabor feature extraction

For extracting features with Gabor filters, each point in the ear image is represented by local Gabor filter responses. A 2-D Gabor filter is obtained by modulating a 2-D sine wave with a Gaussian envelope. The 2-D Gabor filter kernel is defined by:

$$f(x,y,\theta_k,\lambda)=\exp\left[-\frac{1}{2}\left\{\frac{(x\cos\theta_k+y\sin\theta_k)^2}{\sigma_x^2}+\frac{(-x\sin\theta_k+y\cos\theta_k)^2}{\sigma_y^2}\right\}\right] \quad (5)$$

$$.\exp\left\{\frac{2\pi(x\cos\theta_k+y\sin\theta_k)}{\lambda}i\right\}$$

Where $_x$ and $_y$ are the standard deviations of the Gaussian envelope along the *x* and *y*-dimensions, respectively and $_k$ are the wavelength and orientation, respectively. The spread of the Gaussian envelope is defined using the wavelength. A rotation of the $x-y$ plane by an angle $_k$ result in a Gabor filter at orientation $_k$. $_k$ is defined by:

$$\theta_k=\frac{\pi}{n}(k-1) \qquad k=1,2,..,n \quad (6)$$

where n denotes the number of orientations. The Gabor local feature at a point (*X,Y*) of an image can be viewed as the response of all different Gabor filters located at that point. A filter response is obtained by convolving the filter kernel (with specific λ,θ_k) with the image. Gabor kernels with 8 orientation and 4 scales/wavelengths was used. For sampling point (*X,Y*), the Gabor filter response, denoted as g(.), is defined as:

$$g(X,Y,\theta_k,\lambda)=\sum_{x=-X}^{N-X-1}\sum_{y=-Y}^{N-Y-1}I(X+x,Y+y)f(x,y,\theta_k,\lambda) \quad (7)$$

where $I(x,y)$ denotes an *NxN* greyscale image. Gabor filters at multiple frequencies (λ) and orientations (θ_k) was applied at a specific point *(X,Y)* which produces a set of filter responses for that point, denoted as a Gabor jet. A jet J is defined as the set $\{J_j\}$of complex coefficients obtained from one image point, and can be written as:

$$J_j=a_j\exp(i\phi_j) \; j=1,..,n \quad (8)$$

where a_j is magnitude and ϕ_j is phase of Gabor features/coefficients.

2.5.4 Geometrical Method of Feature Extraction

A 2 step concentric geometrical method of feature extraction based on numbers of pixels that have the same radius in a circle with the centre in the centroid and on the contour topology was used. The algorithm (Choras, 2008) for the feature extraction is presented below:

Step 1: A set of circles with the centre in the centroid is created.

Step 2: Number of circles $N_r$is fixed and unchangeable.

Step 3: Corresponding radiuses are α pixels longer from the previous radius.

Step4: Since each circle is crossed by the contour image pixels, the number of intersection pixels *lr*is counted.

Step 5: All the distances *d* between neighboring pixels is counted in a counter clockwise direction.

Step 6: The feature vector that consists of all the radiuses with the corresponding number of pixels belonging to each radius are built and sum of all the distances between those pixels Σ*d*are calculated.

2.6 Features Selection

The Sequential Floating Forward Selection method (SFFS) was used in order to select the most relevant and discriminating subset of features from the initial one and get rid of the redundant features. The SFFS algorithm is described by the following pseudocode:

1. Initialize feature to empty subset Y = {θ};
2. Find the best feature and update Y_m(*forward*)
   X+= argmin (J(Yk+x))
   AεY$_k$
   $Y_{k+1}=Y_k+X^+$
   K= k+1
3. Find the worst feature(backward)
   x^- = argmin (J(Yk + x))
   aεY$_k$
4. If $J(Y_k- x^-) < J(Y_k)$ then
   $Y_{k+1} = Y_k-X^-$
   K=k-1
   Go to step 4
   else
   Go to step 3
   End if

2.7 Ear Database

The ear database consists of 144 Ear samples taken from 72 subjects along with other attributes like name, physical identity and generated results of the processed images. Sample ear images from database are shown in Fig. 3.

Figure 3: Sample Ear images from database

2.8 Ear Recognition

For successful identification, the system compiles the inter-distance based on the image biometrics for both training images and test images and then compares the inter-distance, the inter-distance *D* is given by:

D= (9)

(X_1, X_2) and (Y_2, Y_2) are coordinates of two intersections. The Euclidean distance *ED* is then calculated using the following formula:

ED = (10)

Where D_T and D_{db} are the test and database ear pattern inter-distances.

The algorithm for the matching is presented below:

1) To match two images (one test image T with another from the database db)
2) The Euclidean distance between the two weight matrices of those images is calculated.
3) A test run of the system is used to set a threshold.
4) If the Euclidean distance is higher than a threshold, the output is an imposter, otherwise system outputs a match.

2.9 Performance Evaluation and Analytical Technique

A GUI is created in Matlab as shown in Fig. 4 for entering and identification of a person. The system is then serially presented with 72 genuine subjects and a set of 72 imposters using each feature extraction algorithm. Four experiments with different parameters altered were then carried out. A quantifiable assessment of the accuracy and other characteristics of the system are then measured using performance metrics: False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR), and Recognition Accuracy.

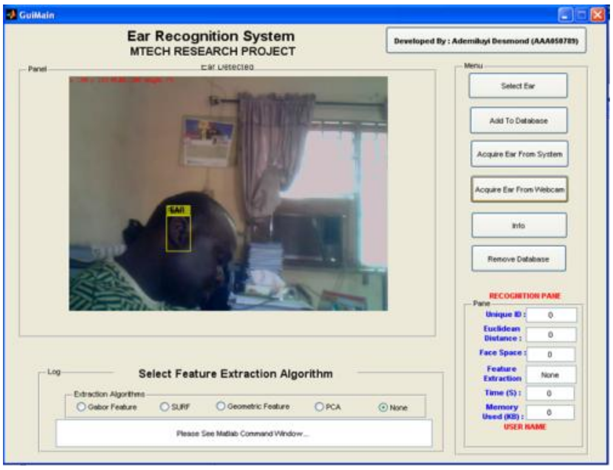

Figure 4: The Developed Ears Recognition System

3. Experimentation and Results

3.1 Experimental Results for PCA Feature Extraction Algorithm

Table 1.1: Performance Analysis of PCA Feature Extraction Algorithm for Normal Pose (Normal Ear Orientation) using 72 Genuine Subjects and 72 Imposters

	Total Matches (Attempt)		
	1st	2nd	3rd
Genuine UserMatches	69	69	71
ImposterMatches	1	0	1
FAR (%)	1.39	0.00	1.39
FRR (%)	4.16	4.16	0.72
GAR (%)	95.84	95.84	99.28
Recognition Accuracy	97.23	97.92	98.95

Table 1.2: Performance Analysis of PCA Feature Extraction Algorithm for Slant Pose (Rotational Orientation at 22.5^o)

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	72	72	72
Total match	64	60	60
FRR (%)	11.11	16.67	16.67
GAR (%)	88.88	83.33	83.33

Table 1.3: Performance Analysis of PCA Feature Extraction Algorithm for Minor Occlusion with Earring.

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	22	22	22
Total match	11	13	9
FRR (%)	50.00	59.09	40.90
GAR (%)	50.00	40.91	59.10

3.2 Experimental Results for Gabor Feature Extraction Algorithm

Table 2.1: Performance Analysis of Gabor Feature Extraction Algorithm for Normal Pose (Normal Ear Orientation) using 72 Genuine Subjects and 72 Imposters

	Total Matches (Attempt)		
	1st	2nd	3rd
Genuine UserMatches	70	70	71
ImposterMatches	3	1	3
FAR (%)	4.16	1.38	4.16
FRR (%)	2.77	2.77	1.39
GAR (%)	97.23	97.23	98.61
Recognition Accuracy	96.54	97.93	97.23

Table 2.2: Performance Analysis of Gabor Feature Extraction Algorithm for Slant Pose (Rotational Orientation at 22.5^o)

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjects	72	72	72
Total match	70	71	69
FRR (%)	2.78	1.39	4.17
GAR (%)	97.22	98.61	95.83

Table 2.3: Performance Analysis of Gabor Feature Extraction Algorithm for Minor Occlusion with Earring.

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	22	22	22
Total match	13	10	14
FRR (%)	40.90	54.55	36.36
GAR (%)	59.10	45.45	63.64

3.3 Experimental Results for Geometric Feature Extraction Algorithm

Table 3.1: Performance Analysis of Geometric Feature Extraction Algorithm for Normal Pose (Normal Ear Orientation) using 72 Genuine Subjects and 72 Imposters

	Total Matches (Attempt)		
	1st	2nd	3rd
Genuine UserMatches	69	69	88
ImposterMatches	9	12	11
FAR (%)	12.50	16.67	15.28
FRR (%)	4.17	4.17	5.56
GAR (%)	95.83	95.83	94.44
Recognition Accuracy	91.67	89.58	89.58

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Table 3.2: Performance Analysis of Geometric Feature Extraction Algorithm for Slant Pose (Rotational Orientation at 22.5^{o})

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjects	72	72	72
Total match	48	51	56
FRR (%)	33.33	29.17	22.22
GAR (%)	66.67	70.83	77.78

Table 3.3: Performance Analysis of Geometric Feature Extraction Algorithm for Minor Occlusion with Earring.

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	22	22	22
Total match	3	5	9
FRR (%)	86.36	77.27	59.09
GAR (%)	13.64	22.72	40.91

3.4 Experimental Results for SURF Feature Extraction Algorithm

Table 4.1: Performance Analysis of SURF Feature Extraction Algorithm for Normal Pose (Normal Ear Orientation) using 72 Genuine Subjects and 72 Imposters

	Total Matches (Attempt)		
	1st	2nd	3rd
Genuine UserMatches	66	67	65
ImposterMatches	19	7	11
FAR (%)	13.89	9.72	15.27
FRR (%)	8.33	6.94	9.72
GAR (%)	91.67	93.06	90.28
Recognition Accuracy	88.89	81.34	87.51

Table 4.2: Performance Analysis of SURF Feature Extraction Algorithm for Slant Pose (Rotational Orientation at 22.5^{o})

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	72	72	72
Total match	65	65	65
FRR (%)	9.72	9.72	9.72
GAR (%)	90.28	90.28	90.28

Table 4.3: Performance Analysis of SURF Feature Extraction Algorithm for Minor Occlusion with Earring.

	Total Matches (Attempt)		
	1st	2nd	3rd
Total Subjets	22	22	22
Total match	17	18	18
FRR (%)	22.72	18.18	18.18
GAR (%)	77.27	81.82	81.82

Average Time and Memory Usage

Table 5: Average Time and Memory Usage over the Four Feature Extraction Algorithms.

Algorithms	Average Comparison Memory (KB)	Average Recognition Time (s)
PCA	77.52	0.66
Geometric feature	57.96	0.66
Gabor feature	24.91	0.93
SURF	44.55	0.83

4. Discussion

The experiments in this research are identification experiments; this section discusses the results of three experiments.

4.1 Experiment on Normal Pose

The first experiment describes the Performance analysis of the Ear Biometric System using the four feature extraction algorithms when the right side image was captured with Normal Pose (Normal Ear Orientation). TABLE 1.1, TABLE 2.1, TABLE 3.1, and TABLE 4.1 describe experimental results for PCA, Gabor wavelet, Geometric and SURF feature extraction techniques respectively under normal ear orientation. PCA and Gabor obtained best recognition rates of 98.95% and 97.23% respectively. Fig. 5 shows the successful identification attempts by genuine users and impostors at the first attempt. The Recognition accuracy of each algorithm is presented in Fig. 6.

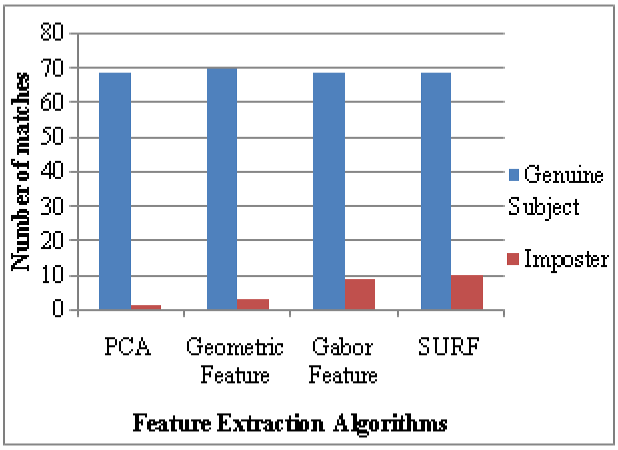

Figure 5: Successful Identification Attempt by Genuine Users and Imposters at First Attempt

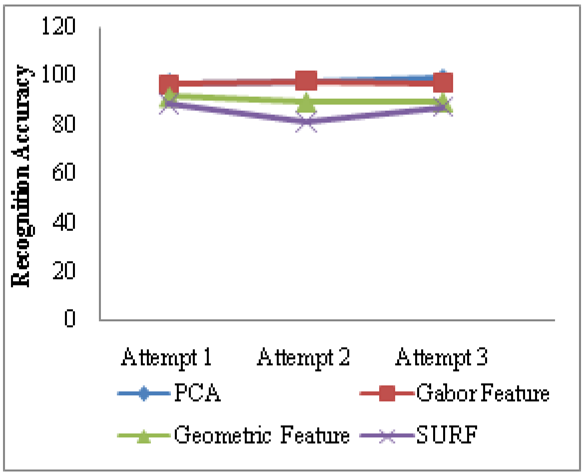

Figure 6: Recognition accuracy by algorithm

4.2 Experiment on Slant Pose (Rotational Orientation at 22.5^{o})

TABLE 1.2, TABLE 2.2, TABLE 3.2, and TABLE 4.2 describe experimental results for PCA, Gabor wavelet, Geometric and SURF feature extraction techniques respectively in the second experiment where the subjects'

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head orientation were tilted to a position, such that that they were facing downwards with the ear at an angle of 22.5° to the horizontal. A total of 72 subjects were presented to the system for recognition. Fig. 7 shows the comparison of the four algorithms on rotational pose at the second attempt. Gabor and SURF feature extraction obtained favorable GAR; however, it is worthy to note that Gabor feature is the only algorithm that out-performs its normal ear orientation, obtaining a GAR above the normal ear pose at 98.61%. A decline in the system performance was observed for Geometric feature extraction technique.

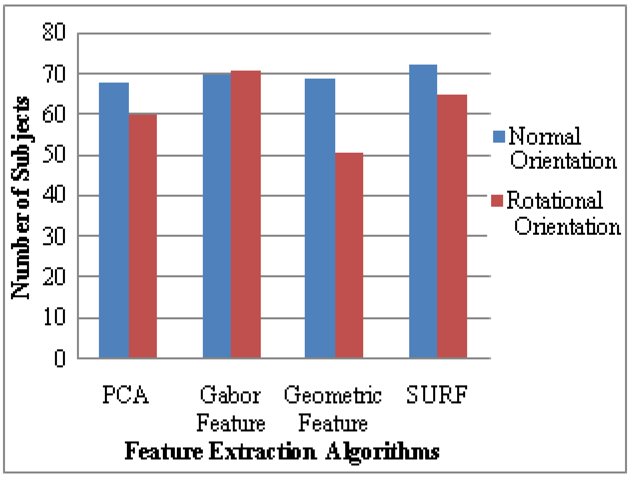

Figure 7: Recognition accuracy for feature extraction algorithms at different orientations for Second Attempt.

4.3 Experiment on Minor Occlusion with Earring

The third experiment considers only minor occlusion of the ear with an earring. TABLE 1.3, TABLE 2.3, TABLE 3.3, and TABLE 4.3 show experimental results for PCA, Gabor wavelet, Geometric and SURF feature extraction techniques respectively when 22 female subjects made attempt at recognition wearing an earring. Fig. 8 indicated that the biometric system performance significantly dropped for all algorithms (except SURF) in the presence of minor occlusion with the earring, the earring constituting an extra edge. This experiment shows SURF is not disturbed by minor occlusion.

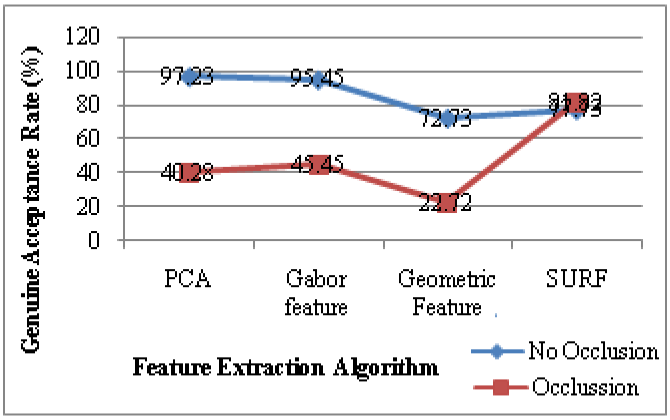

Figure 8: System Performances in the Presence and Absence of Occlusion for Second Attempt

4.4 Memory Used and Matching Speed

TABLE 5 reports the average time and memory usage for the four feature extraction techniques. PCA and Geometric feature had the fastest matching speed with an average time of 0.66s while SURF had 0.83s and Gabor was 0.93s. The average time for the entire four feature extraction algorithm was 0.77s. Fig. 9depicts the average matching time of each Feature Extraction Algorithm.

Fig. 10 correlates the average amount of memory used to the algorithms' recognition accuracy. Almost all the algorithms use more than 40KB of memory; the only exception being Geometric feature, which achieves a recognition accuracy of 91.67% percent using about 24.91KB of memory. The two most accurate algorithms (PCA and Gabor Feature Extraction) show fairly high memory usage of 57.96KB and 77.52KB respectively.

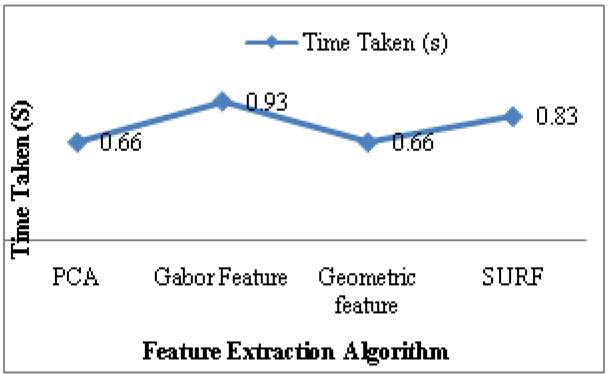

Figure 9: Feature Extraction Algorithm and Average time.

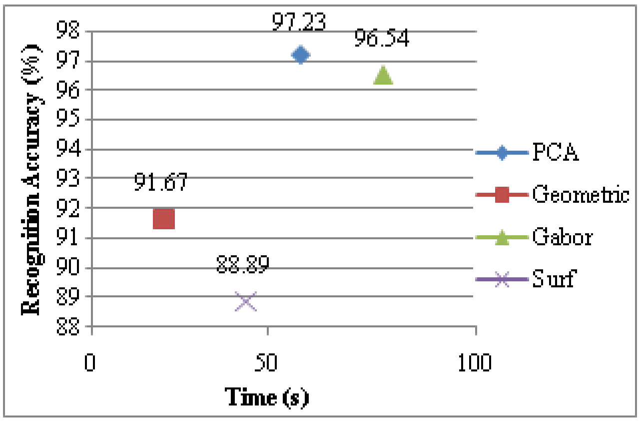

Figure 10: Recognition Accuracy vs. Amount of Memory Used

4.5 Overall Discussion

Table 6 describes the overall comparison of the four feature extraction algorithms using results obtained from the three experiments, matching time and memory usage. PCA and Gabor feature extraction are indeed efficient and strong techniques for feature extraction with normal pose of the ear but required more memory space. In contrast to PCA and Geometric feature, Gabor feature and SURF are insensitive to rotation but unlike Gabor, SURF is effective in the presence of occlusions. Fig.11 describes the recognition capabilities of these feature extraction techniques.

Table 6: Comparison of Feature Extraction Algorithms

Algorithm	*Normal Pose*	*Rotational Orientation (22.5°)*	*Minor Occlusion*	*Average Time*	*Average Memory Used*
PCA	Best	common	Common	Good	Common
Gabor	Good	Best	Common	Bad	Common
Geometric	Good	common	Bad	Good	Best
SURF	Common	Good	Best	Common	Good

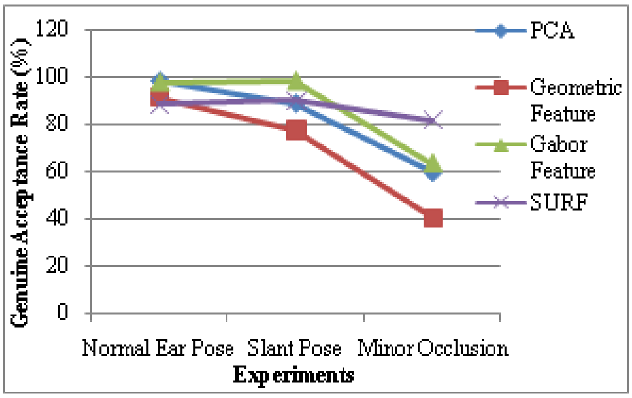

Figure 11: Recognition Capabilities of Feature Extraction Techniques

5. Conclusion and Future Work

This research concluded that PCA and Gabor filter based feature extraction techniques have the best overall performances; however, if restrictions are made on maximum response time, template size, and memory usage, the resulting loss in accuracy can be significant because both approaches required more memory space and Gabor feature extraction taking more time to achieve recognition. However, PCA and Gabor algorithms suffer from matching accuracy in the presence of occlusion while SURF remained indifferent to occlusion. These experimental results allow some observations to be made, but a larger dataset is required to verify these observations and draw any serious conclusions. Speed and recognition accuracy remain important issues, future works could look into several enhancements to improve the speed of these algorithms.

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