A Simple Geometric Approach for Ear Recognition

A Thesis Submitted
in Partial Fulfillment of the Requirements
for the Degree of
Master of Technology

by
Dasari Naga Shailaja

to the
DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY,KANPUR
June 2006

CERTIFICATE

This is to certify that the work contained in the thesis entitled "*A Simple Geometric Approach for Ear Recognition* " by *Dasari Naga Shailaja* has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

June, 2006

Prof. Phalguni Gupta
Department of Computer Science & Engineering,
Indian Institute of Technology Kanpur
Kanpur-208016.

Abstract

With the development of more and more systems which provide service based on the identity of a person the importance of personal identification is growing. Providing authorized users with secure access to the services is a challenge to the personal identification systems. There are several conventional means for personal identification which include passports, keys, tokens, access cards, personal identification number (PIN), passwords. Unfortunately, passports, keys, access cards, tokens, can be lost, stolen or duplicated, and passwords, PINs can be forgotten, cracked or shared. These drawbacks cause a great loss to the concerned. A reliable solution is required to fill the loopholes of the conventional personal identification methods. Biometric systems are proving to be an efficient solution to this problem. These systems are based on the human traits which, unlike conventional methods, cannot be lost, stolen forgotten or duplicated. Biometric systems are truly an evolving means of personal identification.

Ear is a relatively new class of biometrics. It has been suggested by the researchers that the shape and features of ear are unique for each person and invariant with age, which has made ear a biometric trait. Several approaches have been proposed for ear recognition. In this thesis a simple two-stage scale and rotation invariant geometric approach which is based on the concept of max-line, the longest line that has both its end points on the edges of the ear, has been proposed.

Contents

List of Figures

Chapter 1

Introduction

With the development of more and more systems which provide service based on the identity of a person the importance of personal identification is growing. For example many a times identity of a person needs to be proven like, to use an ATM, entering an organization, e-commerce, to gain access to a bank account. Providing authorized users with secure access to the services is a challenge to the personal identification systems. There are several conventional means for personal identification which include passports, keys, tokens, access cards, personal identification number (PIN), passwords. Unfortunately, passports, keys, access cards, tokens, can be lost, stolen or duplicated, and passwords, PINs can be forgotten, cracked or shared. These drawbacks cause a great loss to the concerned. A reliable solution is required to fill the loopholes of the conventional personal identification methods.

Biometric systems are proving to be an efficient solution to this problem. These systems are based on the human traits which, unlike conventional methods, cannot be lost, stolen forgotten or duplicated. Biometric systems are truly an evolving means of personal identification.

1.1 Biometrics

Biometrics is the study of automated methods for recognizing a person based on his physical or behavioral characteristic. Biometric systems can be divided into two categories- identification systems and verification systems. Identification systems tell "who you are?" and verification system tell "are you the one who you claim to be?"

The idea of biometric identification is very old. The methods of imprints, handwritten signatures are still in use. The photographs on the identification cards are still an important way for verifying the identity of a person. But developing technology is paving the way for automated biometric identification and is now a highly interested area of research.

There are different human traits that can be used by a biometric system. Some of them are face, fingerprint, iris, voice, speech, hand geometry and retina. The following parameters are used to decide whether a human trait can be used as a biometric or not.

Universality how common the trait is found in each individual

Uniqueness how well the trait separates an individual form other

Permanence how the trait changes with age

Collectability how easy it is to acquire the trait

Performance indicates the accuracy, speed, and robustness of the biometric system built using the trait.

Acceptability indicates the degree of approval of a technology by the public in everyday life.

Circumvention is how easy it is to fill the authentication system. In this thesis a new approach is proposed which uses the shape of the ear for recognition.

1.2 Working of a Biometric System

A biometric system mainly consists of two processes - enrollment process and verification/identification process. Figure 1.1 shows a generic biometric system.

1.2.1 Enrollment Process

Before a biometric can be used for identification, a trusted sample of the biometric trait should be captured using a biometric sensor and is preprocessed so that the approach used for recognition can be applied to the sample. Feature Extractor generates an expressive form of the sample called a template and it is stored in the database or recorded on a magnetic card and issued to the user. Typically several samples are collected to increase the accuracy of the system.

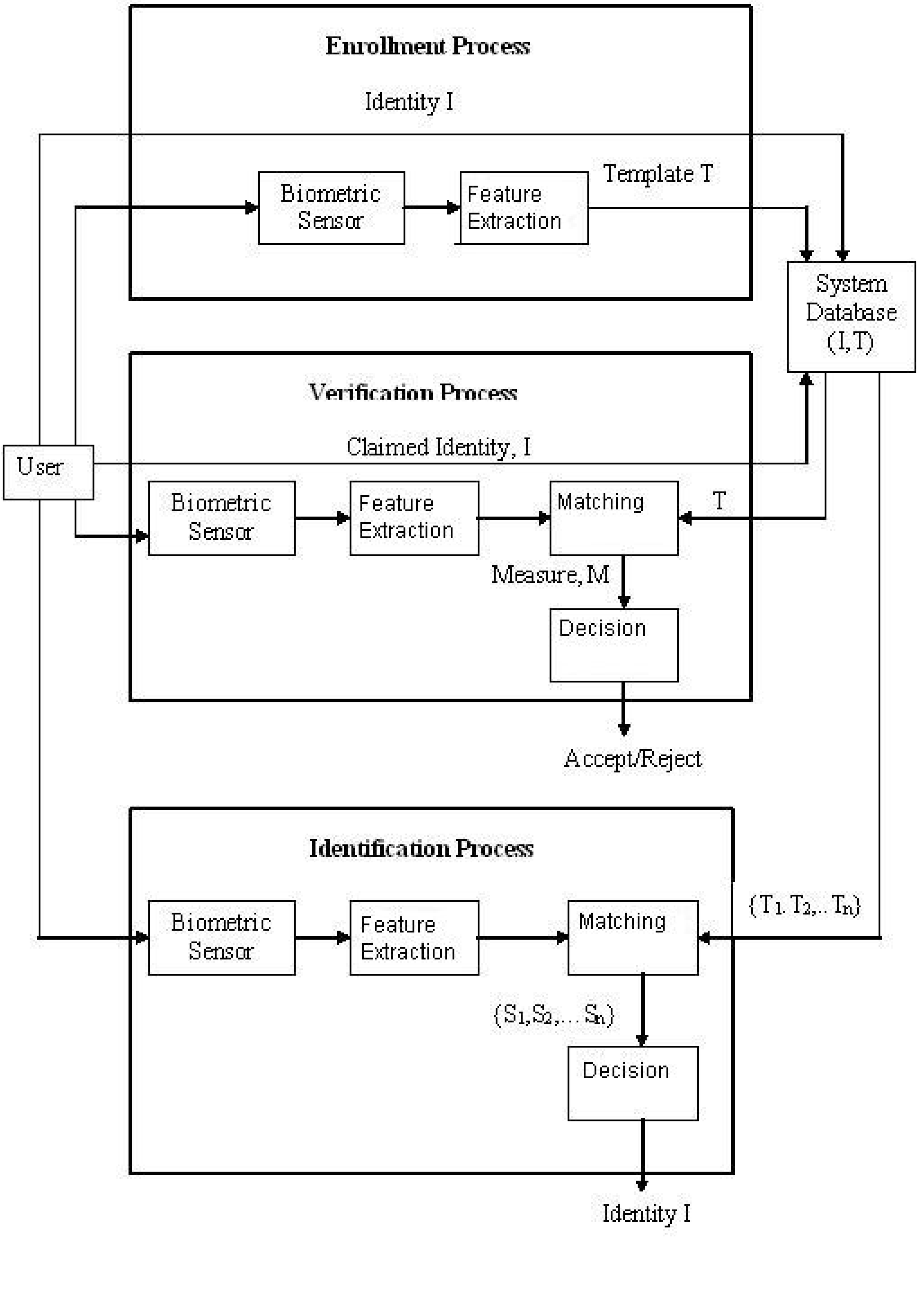


Figure 1.1: A generic Biometric System

1.2.2 Verification Process

At the time of verification a sample of the biometric is captured and features are extracted from the sample. The new template is matched against the stored template of the user in the database and a measure M is calculated. The decision module accepts or rejects the claim of the user using the measure M.

1.2.3 Identification Process

This process finds out who the user is. A sample of the biometric trait is captured using the sensor and features are extracted. The new template is matched against all the templates in the database producing a score S for each template. Depending on the scores the decision module decides who the user is. It may be possible that the exact match cannot be found, in which case few top best matches will be provided.

1.3 Biometric System Performance

Due to the environmental variations, noise and different positioning of the biometric sensor, it is not possible that two images acquired at different points of time are exactly identical. Therefore a matching algorithm is required which computes a similarity score of the two images and decides if the two images are of the same subject by comparing the similarity score with an acceptance threshold. It is possible that sometimes the output of a biometric system may be wrong. The performance of a biometric system is given in terms of false acceptance rate (FAR), false reject rate (FRR), equal error rate (EER) or crossover error rate (CER).

False Reject Rate is the percentage of times the system rejects an authorized user.

False Accept Rate is the percentage of times the system accepts an unauthorized user.

FAR and FRR are closely related. They depend on the acceptance threshold which is used to set the desired security level. If the threshold is raised false acceptance rate decreases but the false rejects increase, since it will be harder for the live samples to match the higher demands. The reverse is also true. If threshold is decreased, FRR decreases at the same time FAR increases.

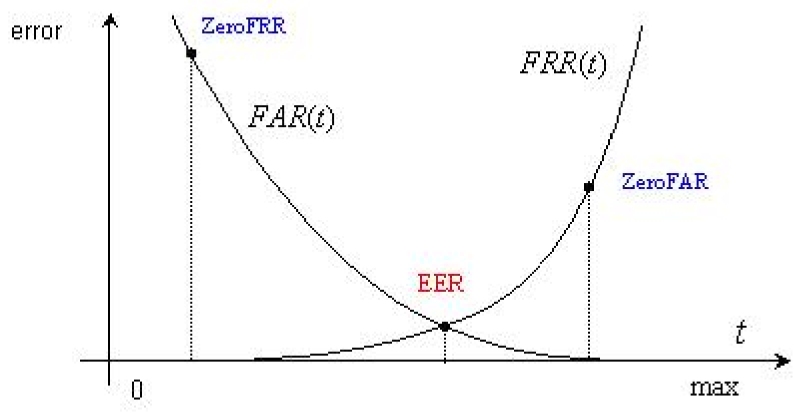


Figure 1.2: A typical performance curve

Equal Error Rate, also known as crossover error rate, is the point where the false acceptance rate and false reject rate are equal. It can be seen from Figure 1.2, how FAR and FRR are linked. While trying to set the acceptance threshold value it is usually a better choice to select ERR to get optimal performance. But it is always not the case. It depends on the biometric application. For example in an ATM it is better to risk few false accepts rather than the annoyance of the customers if the system rejects authorized users.

For an effective comparison of different systems, a threshold independent description is required. Receiver operating characteristics (ROC) is an example to such a description. It is a plot showing False accept rate along the X-axis and genuine accept rate along the Y-axis. A good ROC curve should be more towards the upper left side of the graph.

There are other issues as well to be considered when evaluating a system's performance, such as time. For example one cannot use a biometric system in an ATM if it takes several minutes to verify a user.

1.4 Biometric Technologies

There are two types of biometric methodologies-physical and behavioral. Figure 1.3 shows some of the most used biometric characteristics and the category into which they fall. Behavioral try to identify a user based on some sort of behavior that is typical for a user like the way they walk, or the way they hold the pen while writing or the way they press the keys while entering the PIN etc. On the other hand, physiological methods try to identify the user by some sort of physical trait that is typical to the user. Examples include fingerprint, face, iris, retina etc.

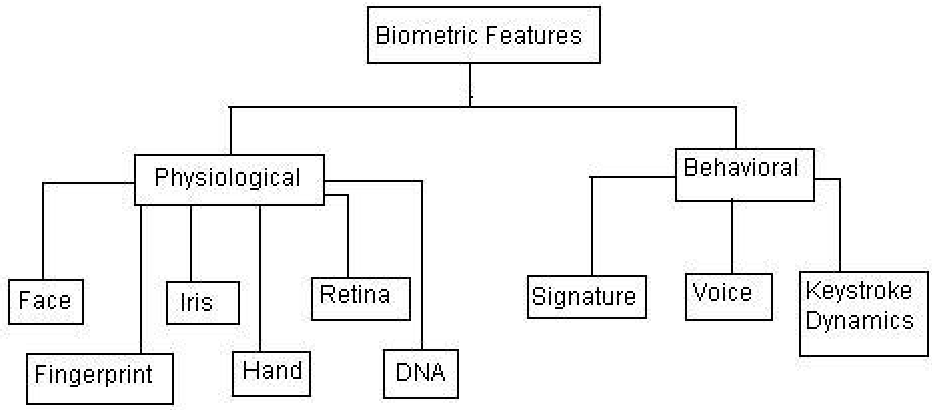


Figure 1.3: Different types of biometric features

Given below are some of the biometric technologies including those which are still at the research stage.

1.4.1 Face Recognition

Face recognition is a Biometric technology that uses an image or series of images either from a camera or photograph to recognize a person. It does not require a person's cooperation. Face recognition is completely oblivious to differences in appearance as a result of race or gender differences and is a highly robust Biometrics. However, the face changes considerably with age, and even due to make-up and expression changes. Face recognition systems can be divided into two main categories. Systems used to verify the identity of a person in a known environment at a fairly constant distance and systems that try to identify a person from a group of people in a dynamic environment and at a random distance[3, 27].

1.4.2 Fingerprint

Fingerprint recognition is an extremely useful biometrics technology since fingerprints have long been recognized as a primary and accurate identification method. It is as a direct result of this recognition, that large fingerprint databases can be found within law enforcement agencies the world over. Fingerprint technology can be used for both verification (1:1) matching as well as for Identification (1: n) matching. Fingerprints have very high persistence but may be unhygienic, as contact with a sensor is required. Fingerprint recognition systems based on both the global appearance and minutiae of the friction ridges have been developed and laser scanning systems are also in use[19, 14].

1.4.3 Signature

The handwritten signature is a behavioral biometric. Signatures have been used to verify transactions for centuries and are therefore a well-established method. Automatic signature verification systems do not only examine the appearance of the signature, they also examine the dynamics of the writing. How hard is the pencil pressed against the surface during different phases of the signature? How fast are the different letters written? How long time does it take to write the whole signature? How and when is the letter ”t” crossed? There are also several more behavioral biometrics that can be used to verify a user identity using signatures[21, 9].

1.4.4 Iris Recognition

The iris at first seems to be a bad choice for a biometric. But if observed closely, it has considerable texture detail that makes it a good biometric trait. Iris recognition is considered to be the most accurate biometric technology and is being used very effectively all over the world. Iris recognition technology is safe, accurate and works with high speed without sacrificing accuracy[15, 16].

1.4.5 Retina

The retina is the layer of blood vessels at the back of the eye. The biometric technology based on retinal scanning is known for low FAR and have therefore been used for years in very high security facilities. But it requires considerable cooperation from the subject as it is inconvenient as intrusive. The retinal scanner requires that the subject should stand still during the scanning process.

1.4.6 Hand Geometry

Hand Geometry is also one of the most famous biometric. There are two types of hand geometry based systems. One type uses the entire hand for recognition and another type uses only two fingers. It is based on the fact that for every person hand is shaped differently and it does not change significantly with time. The shape and length of the fingers and knuckles are used. Hand recognition systems are especially useful in outdoor environments and it also has the advantage that the templates are very small in size as small as 9 bytes[18].

1.4.7 Voice Recognition

Voice recognition systems work by analyzing the waveforms and air pressure patterns produced while a person talks. These systems may use the characteristics of an individual voice or some pre-arranges words. Voice is one of the most convenient biometric but is not reliable due to bad accuracy. Voice can be mimicked and also a person with a cold or throat problems may face problems using the voice recognition system as it may be rejected[17].

1.4.8 DNA

DNA stands for Dioxyribo Nucleic Acid and is found in every cell of an individual. It is completely unique for every person and is most reliable when a positive identification is required. But as it requires extensive testing, it is not the most cost efficient biometric trait.

1.4.9 Keystroke Dynamics

Keystroke dynamics is a very new technology and can be said as an extension to passwords and PINs. It is a behavioral biometric. It works by analyzing the way one types the keys, the factors like, the time taken by the user to find the keys, the speed of typing .But the method is sensitive to the mood of the user. And the typing dynamics all change as the user is used to typing[1].

Chapter 2

Ear Biometrics

Ear is a relatively new class of biometrics. Ear features have been used for many years in the forensic sciences for recognition. Ear is a stable biometric and does not vary with age. Ear has all the properties that a biometric trait should have, i.e. uniqueness, universality, permanence and collectability.

2.1 Anatomy of the Ear

Ear does not have a completely random structure. It has standard parts as other biometric traits like face. Figure 2.1 shows the standard features of the ear. Unlike human face, ear has no expression changes, make-up effects and moreover the color is constant through out the ear.

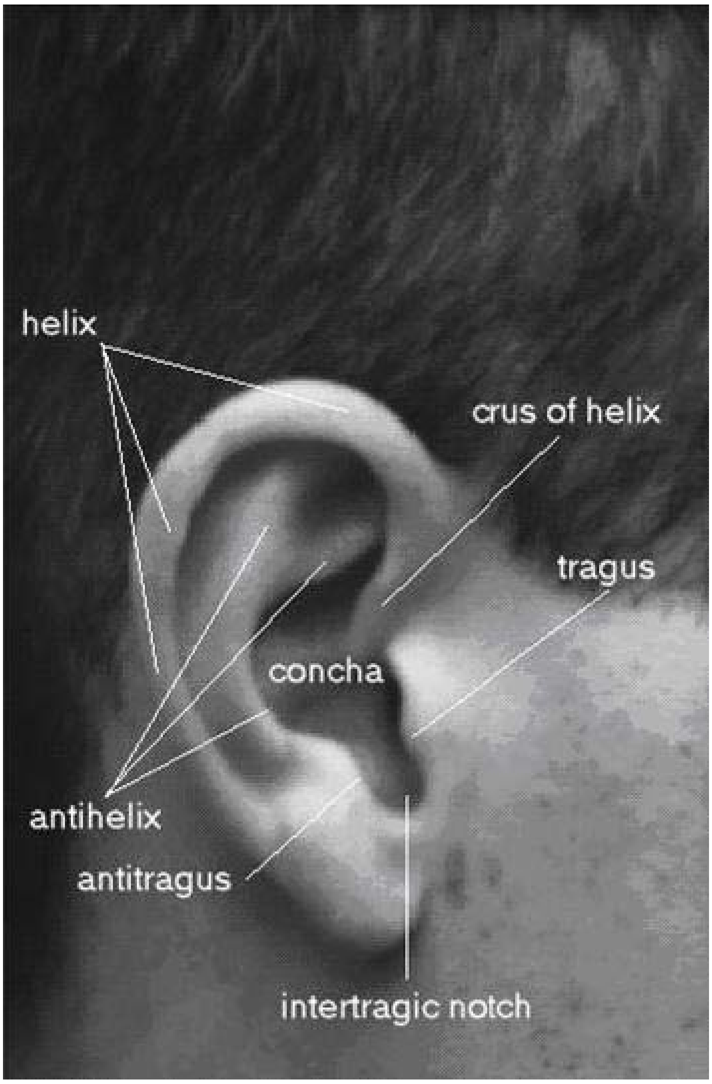


Figure 2.1: Anatomy of the ear

2.2 Literature Review

Studies say that ear biometrics is comparable to face biometrics and is also found to give better results than face. Many approaches have been proposed for ear recognition. The study of ear recognition begun after the work of Iannarelli[13]. He claims that the ear is unique to each individual. He has classified the ear by dividing it into eight parts as shown in Figure 2.2. The Iannarelli's system is based upon twelve measurements taken around the ear using the marks shown in Figure 2.2. They are measured by placing a transparent compass over an enlarged photograph of the ear. The transparent compass has eight spokes at equal 45° intervals. The reference line should be such that its top touches the intersection between the antihelix and crus of helix and bottom touches the innermost point on the tragus. For the purpose of normalization, the photograph should be enlarged until a second reference line exactly spans the concha from top to bottom.

Burge and Burger[4] proposed an approach for automating ear biometrics. According to the approach proposed, each subject's ear is modeled as an adjacency graph built from Voronoi diagram of its curve segments. They claim that the novel graph matching based algorithm for authentication that is proposed, is suitable for passive identification. Another approach is proposed by Moreno and Sanchez and Velez[2]. This approach combines the results of several neural classifiers which use the information obtained from ear shape and wrinkles, and macro features extracted by compression network.

Another significant approach is proposed by Hurley, Nixon and Carter[11, 12]. They have proposed an approach based on force filed transformations in

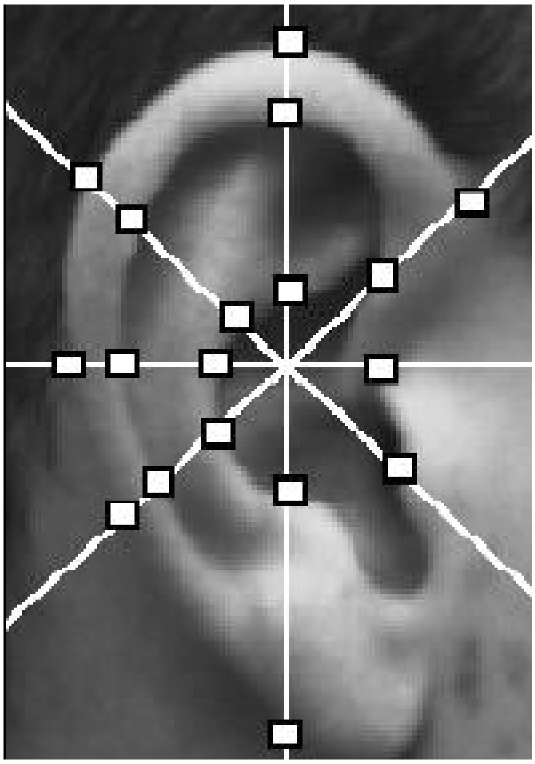


Figure 2.2: Iannarelli ear measurements

which the image is treated as an array of Gaussian attractors that act as the source of a force field. The ear is described using small number of wells and channels which are located by using the directional properties of the force field.

Victor, Bowyer, Chang and Sarkar[6, 22] have evaluated the face and ear recognition using principal component analysis (PCA), a dimensionality reduction technique which preserves the variation in the dataset. They have found that recognition performance is not much different for the ear and the face. They claim that the multimodal recognition using both the ear and the face results in significantly better performance than individual biometrics.

Very recently approaches have been proposed for 3D ear recognition. Yan and Bowyer have proposed an iterative closest point (ICP) based approach[23]. A novel approach called "Pre-computed Voxel Closest Neighbors" is presented to improve the speed of the original ICP algorithm. They have also empirically evaluated 2D and 3D ear biometrics[26, 25] which says that the ICP-based approach outperforms the PCA based 2D ear recognition. Various combinations of algorithms for 2D and 3D ear recognitions were experimented and found to give better results than a single biometric[24]. Another approach for 3D ear recognition is proposed by Chen and Bhanu[7]. A two-step ICP algorithm for matching 3D ears is given.

Pun and Moon have summarized the various approaches proposed for ear recognition[20]. Choras has given an approach by using geometric method of feature extraction[8]. The method works by finding the centroid and creating circles centered at the centroid and then finding the intersection points of the circles and the edges of the ear. The number of intersection points and the distance between them are then used for classification.

Chapter 3

The Proposed Approach

Several approaches that were proposed for ear recognition were seen in the last chapter. A simple two-stage geometric approach based on the concept of max-line, which is scale invariant, rotation invariant is proposed in this chapter. Ear Recognition can be divided into four major steps-image acquisition, pre-processing, feature extraction, and two-stage classification. Figure 3.1 shows the block diagram of the approach.

3.1 Image Acquisition

The side face images have been acquired using Sony DSC-P10 camera in the same lightening conditions with no illumination changes. All the images are taken from the right side of the face with a distance of 15-20 *cms* between the face and the camera. The images should be carefully taken such that outer ear shape is preserved. The less erroneous the outer shape is the more

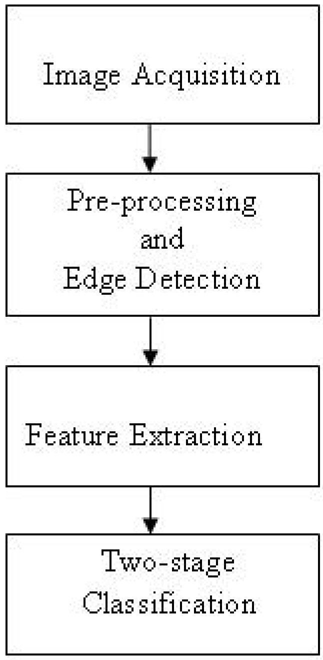


Figure 3.1: Major steps of the approach

accurate the results are. Figure 3.2 shows an example image which preserves the outer shape of the ear.

3.2 Image Pre-processing

The ear part is manually cropped from the side face image and the portions of the ear which do not constitute the ear are colored black leaving only the ear. The colored image is then converted to grayscale image. Figure 3.3 shows the grayscale image which is obtained by cropping the ear part from

Figure 3.2: A side face image acquired

the image in Figure 3.2.

3.2.1 Edge Detection and Binarization

The edge detection and binarization is done using the well known canny edge detector [5]. If w is the width of the image in pixels and h is the height of the image, the canny edge detector used takes as input an array $w * h$ of gray values(float values) and sigma(standard deviation) and outputs a binary image with a value 1 for edge pixels, i.e., the pixels which constitute an edge, and a value 0 for all other pixels. Figure 3.4 shows a grayscale image and its corresponding edge detected binary image obtained from canny edge detector.

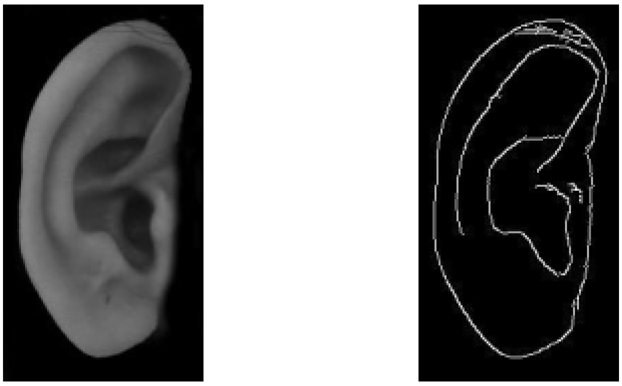
It can be observed that the edge detected image has many noisy edges.

Figure 3.3: Cropped grayscale image

These edges are to be removed leaving an image which has only those edges of our interest i.e. edges which can be used for the recognition purpose. This can be used by connected component labeling [10]. The edges in the binary edge detected image are labeled i.e. each edge is given a unique label. All edges with length less than some threshold value are removed. The length of an edge can be defined as the number of pixels that constitute the edge. Figure 3.5(a) shows a binary edge detected image with noisy edges and Figure 3.5(b) shows its corresponding image in which noisy edges have been removed image.

3.3 Feature Extraction

In this approach the features extracted are all angles and these features are divided into two vectors. The first feature vector is found using the outer shape of the ear i.e. the outer edge, and the second feature vector is found using all other edges. To find the angles, the terms max-line and normal



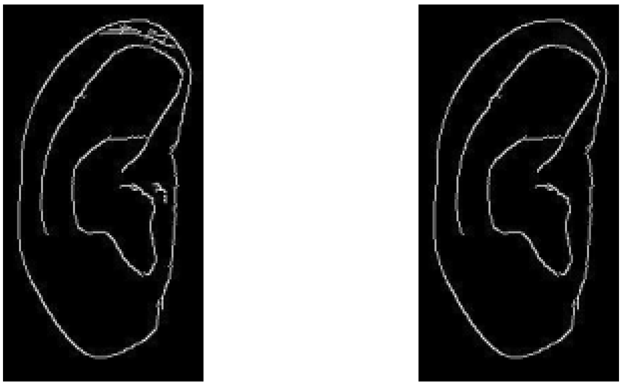
(a) (b)

Figure 3.4: Grayscale image and its corresponding Edge detected binary image

lines are to be understood.

Max-line can be defined as the longest line that can be drawn with both its endpoints on the edges of the ear. The length of a line is measured in terms of Euclidean distance. It can be easily understood that the max-line has both its end points on the outer edge of the image. As the whole approach is based on the max-line it should be found very carefully and with minimum error. There may arise a doubt if this line is unique. The chances are very less. If there are more than one line, features corresponding to each max-line are to be extracted.

Normal lines are the lines which are perpendicular to the max-line and which divide the max-line into $(n + 1)$ equal parts, where n is a positive integer.



(a) (b)

Figure 3.5: Images with and without noisy edges

Figure.3.6 shows an image with max-line m, normal lines $l_1, l_2, l_3, \ldots, l_n$ named from top to bottom, center of the max-line c. Let $p_1, p_2, p_3, \ldots, p_n$ be the points where the outer edge and the normal lines intersect. It is assumed that the outer edge is continuous.

The first feature vector FV1 can be defined by.

$$FV1 = [\theta_1, \theta_2, \ldots, \theta_n]$$

where θ_i is the angle corresponding to point p_i, for $i = 1ton$, that is, θ_i is the angle made by the line segment joining p_i and c and the line segment joining m_1 and c, where m_1 is the upper end point of the max-line. All angles should be measured in the same direction either clockwise or counter clockwise. The angle θ_1 may vary from 0 to π. Figure 3.7(a) shows an ear image with points $p_1, p_2, \ldots, p_n$, max-line m and the angle θ_1.

The second feature vector denoted by FV2 is similarly calculated but the

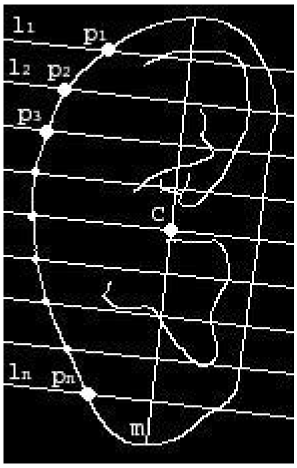


Figure 3.6: Image with max-line and normal lines

points of interest vary. All the points where the edges of the ear and the normal lines intersect are considered except the points that were used for first feature vector. Note that the angles may vary from 0 to 2π. Figure 3.8(a) shows an image with max-line, normal lines and points considered for second feature vector are highlighted. Figure 3.8 shows a second feature vector point and its corresponding angle.

3.4 Classification

Classification is the task of finding a match for a given query image. In this approach classification is performed in two stages. In first stage the first feature vector is used while in the second stage the second feature vector is used. It was seen that the first feature vector consists of n angles corresponding to n points of the outer edge.

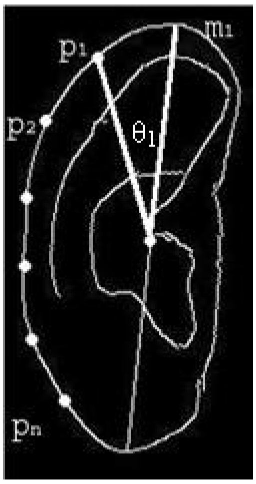


Figure 3.7: Image showing the angle θ_1

Let $FV1_1 = [\theta_1, \theta_2, \ldots, \theta_n]$, $FV1_2 = [\alpha_1, \alpha_2, \ldots, \alpha_n]$ be the first feature vectors of two images that are to be matched. Using these vectors two measures namely difference, d_1, and number of points matched, w_1, are calculated. d_1 is given by the equation

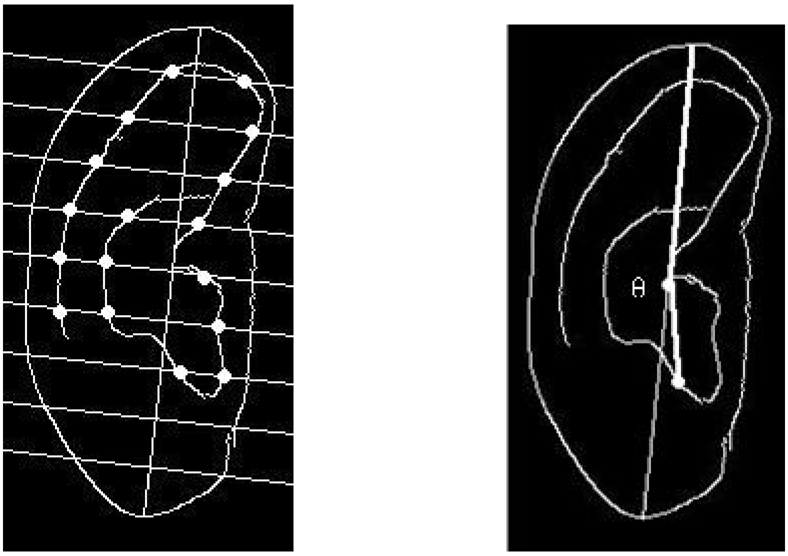
$$d_1 = \sum_{i=1}^{n} |\theta_i - \alpha_i|$$

where $|\ |$ represents absolute value. w_1 is the number of points that are matched. Two points are said to be matched if their corresponding angles are same with some error e. w_1 is given by the equation

$$w_1 = \sum_{i=1}^{n} x_i$$

where $x_i = 1$ if $|\theta_i - \alpha_i|$ is less than some threshold else $x_i = 0$.

Two images are said to be matched with respect to the first feature vector if d_1 and w_1 are less than some threshold values.



(a) (b)

Figure 3.8: (a)Image showing the second feature vector points (b) Image showing one of the angles

In the next stage two points are said to be matched if their angles are approximately same and also they correspond to the same normal line. Let w_2 denote the number of points that are matched. But as the size of second feature vector is not fixed the percentage of matched points, pt, is calculated by the equation

$$pt = \frac{w_2}{min(v_1, v_2)} * 100$$

where v_1, v_2 are the sizes of second feature vectors of the two images.

Two images are said to be matched finally if they are matched with respect to first feature vector and pt is greater than some threshold value.

3.4.1 Advantage of Two-stage Classification

A given query image is first tested against all the images in the database using first feature vector. Only the images that are matched in the first stage are considered for the second stage of classification. As the size of first feature vector is less, that is n, number of normal lines, only n comparisons are needed for the first stage of classification. In the second stage of classification, $m * n$ comparisons are required, assuming m points for each normal line. Let I be the number of images in the database. If the classification is single stage the total number of comparisons required are $I * ((n) + (m * n))$, that is for each of I images, n comparisons for first feature vector and $m*n$ comparisons for second feature vector. If the classification is divided into two stages the effective number of comparisons required reduces to $I*n+I_1*(m*n)$, where I_1 is the number of images that are matched with respect to the first feature vector. Therefore, we save $(I - I_1) * (m * n)$ comparisons. As I_1 is very less compared to I, less than half, dividing classification into two stages greatly reduces the time taken for classification.

3.5 Number of Normal Lines

Selecting the value for n is also a crucial aspect in this approach. A greater value of n increases the accuracy but also increases the space requirement the time taken for classification as more number of features are to be compared. A very large value of n may also decrease the accuracy. A smaller value of n reduces the accuracy. Therefore an optimal value should be selected which satisfies all the three requirements of space, time and accuracy.

3.6 Scale and Rotation Invariance

Since the relative angles are considered rather than absolute angles the approach is scale and rotation invariant. Since the max-line does not vary with scale and rotation. The angles also do not vary with scale and rotation. In the next chapter this is explained in detail using examples.

Chapter 4

Experimental Results

The proposed approach is tested on a database of 160 images of 80 subjects, two images of each subject. The test data consists of 80 images, one image of each person from the database and these are tested against all the images in the database. The value of n, the number of normal lines is fixed as 19. Figure 4.1 justifies the selection of value for n. As it is stated previously, the value of n should be selected such that it satisfies all the three requirements of space, time and accuracy. It can be seen in Figure 4.1 that the equal error rate (EER) is less when the value of n is 19 or 21. As seen in Chapter 1, the less the equal error rate, the more the accuracy of the approach. A less value of n requires less space and time for classification, as we have seen in Section 3.5, therefore, the value of n is fixed as 19.

As the size of first feature vector is equal to the number of normal lines, the first feature vector is of size 19. We assume that for every normal line there are at most five points which can be considered for second feature

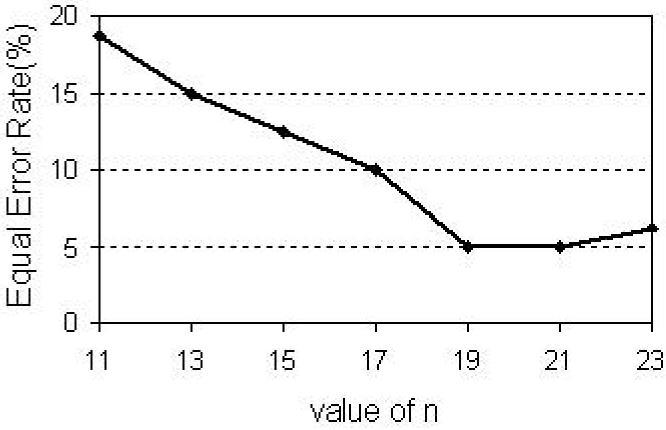


Figure 4.1: Plot showing how the accuracy changes with the value of n

vector. If there are more than five points only first five points from left to right are considered and the remaining are ignored. Therefore the size of second feature vector is 19*5 which is equal to 95. Therefore combined for each image 19+19*5 which is equal to 114 angles are stored. All the angles are measured in radians. Since double datatype requires more space and also more time for computation all the angles are converted to integer type.

The result of the experiment is shown in Figure.4.2. White point shows a match. It can be seen that out of 80 images four images are falsely rejected(four missing points) and four images are falsely accepted(four points far from the diagonal).The EER (equal-error rate) of the experiment is 5%. It is observed that after the first stage of classification the search space reduces by 80% to 98%. Figure 4.3 shows the ROC curve for the results of the experiment. It can be seen that when the false acceptance rate is 0.001 which is very small the genuine acceptance rate is 77.5%. Therefore the curve lies in the upper left side of the graph which is the property of a good ROC curve.

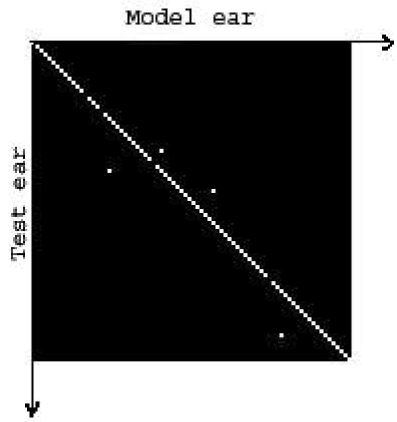


Figure 4.2: Plot showing the result of the experiment

Some test images and some model images are shown in Figure.4.4 and Figure.4.5. The first image in each row is a test image and it is matched against all other images in the same row. The second image in each row is of the same subject as the first image. Values of d_1, w_1, pt are shown for each model ear. Recollect that d_1, w_1, pt are the difference of angles of first feature vector, the number of first feature vector points that are matched and percentage of matched second feature vector points respectively. The first row of Figure.4.5 shows the case where the image is falsely rejected and second row shows the case where the image is falsely accepted.

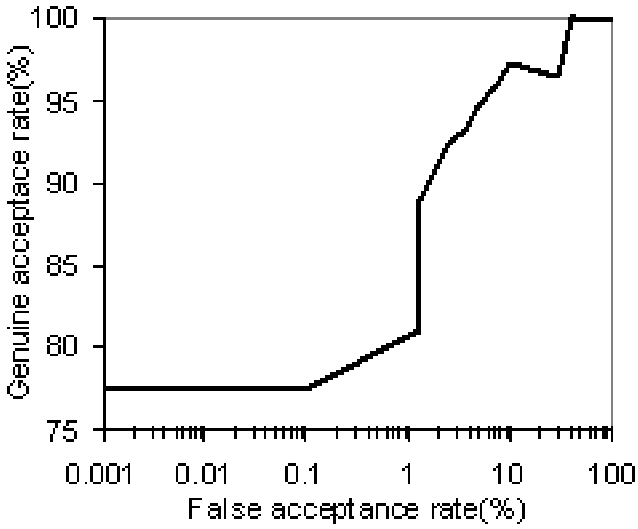


Figure 4.3: ROC curve drawn using the result of the experiment

4.0.1 Scale and Rotation Invariance

Since the relative angles are considered rather than absolute angles the approach is scale and rotation invariant. Figure 4.6 shows six different images where Figure 4.6 is obtained by rotating the Figure 4.6(a) by 10° clockwise, Figure 4.6(c) by rotating the Figure 4.6(a) anticlockwise by 10°, Figure.4.6(e) is obtained by scaling the Figure 4.6(a) by a factor 1.3 and Figure 4.6(f) by scaling by a factor 0.4. Figure 4.6(d) is image of a different subject.

It can be seen from the table in Figure 4.6 that the first feature vector values are almost the same for images (a), (b), (c), (e), and (f). This shows that the approach is scale and rotation invariant. It can also be seen from the table there is much difference between the first feature vector values of

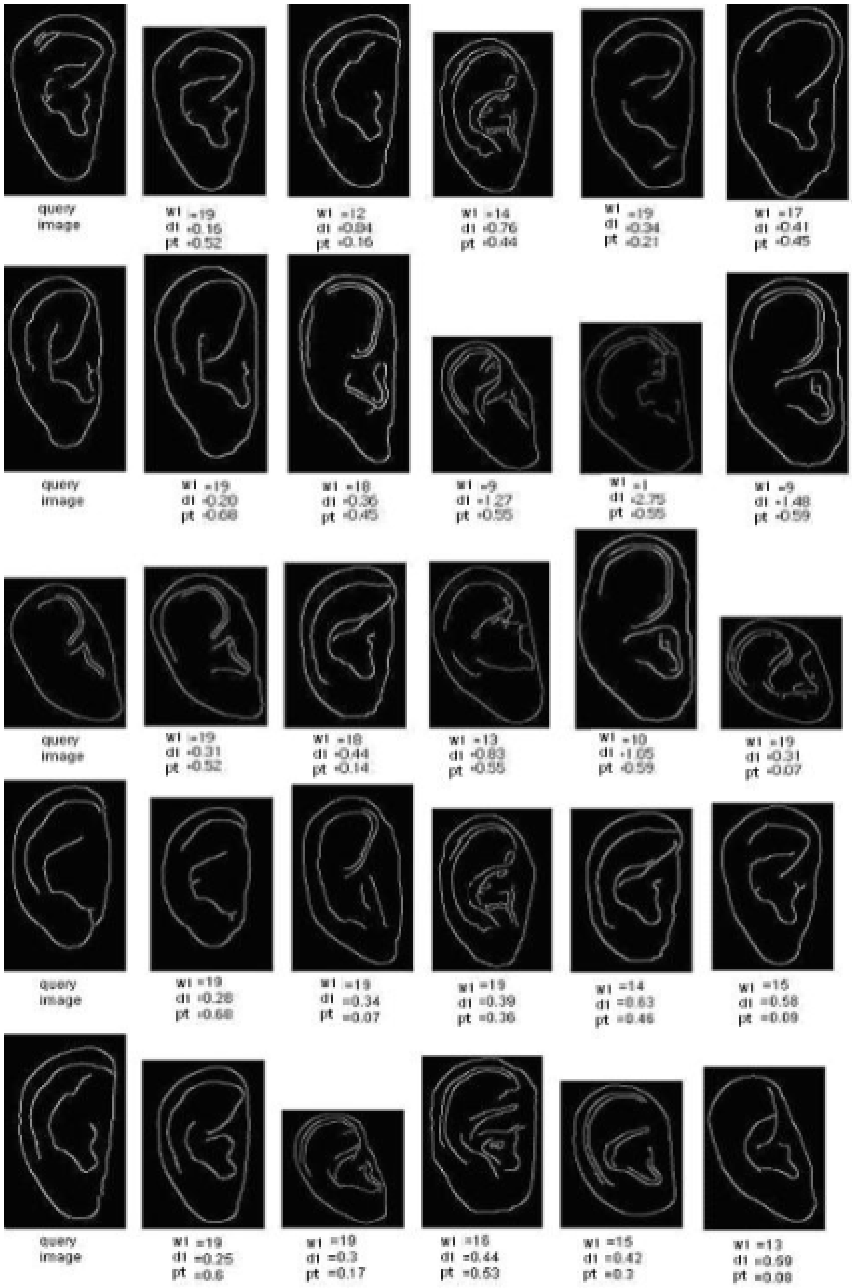


Figure 4.4: Experimental values for some test ears and model ears. First image in each row is matched against all other images in the same row.

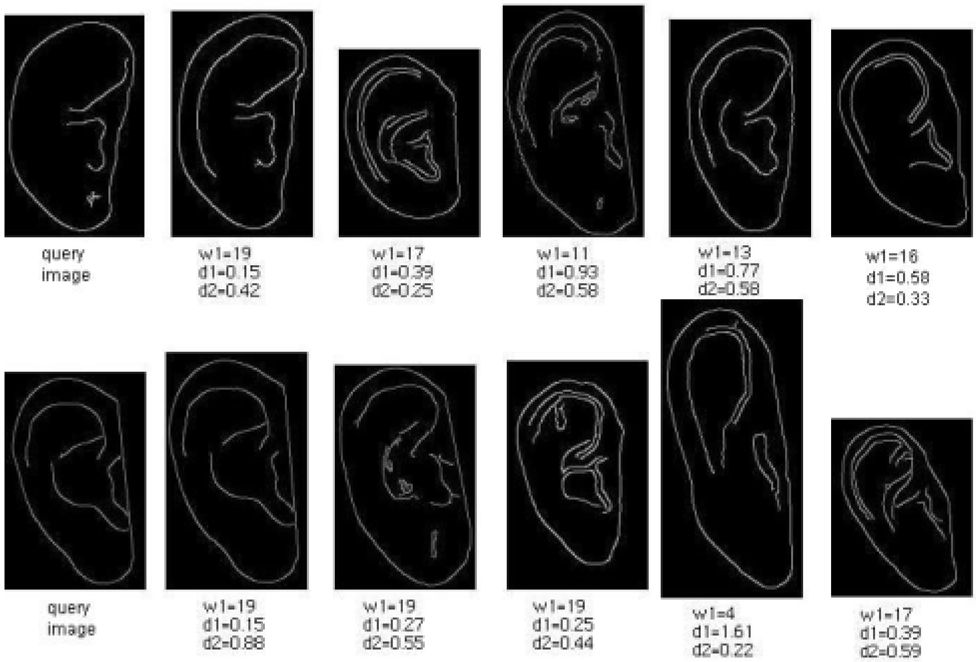
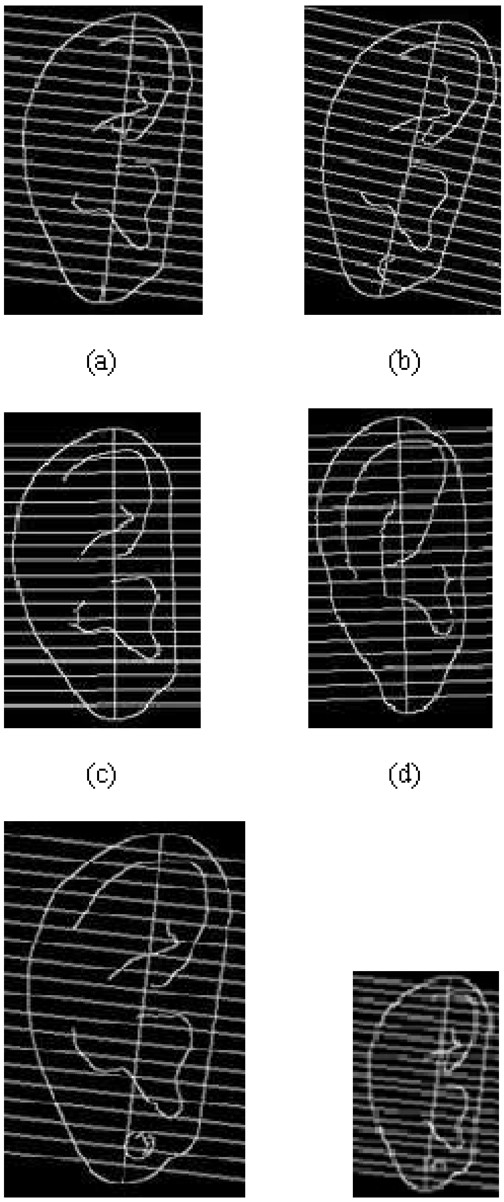


Figure 4.5: Examples of falsely accepted ear and falsely rejected ear.

image (d) and the image (a) leading to a greater value of d_1 and also observe w_1, the number of points that are matched.



(a) (b) (c) (d) (e) (f)

	(a)	(b)	(c)	(e)	(f)	(d)
1	0.28	0.26	0.32	0.28	0.28	0.29
2	0.46	0.42	0.49	0.46	0.44	0.43
3	0.61	0.58	0.63	0.61	0.60	0.56
4	0.74	0.72	0.76	0.75	0.74	0.69
5	0.86	0.84	0.89	0.87	0.87	0.81
6	0.99	0.98	1.01	0.99	0.99	0.93
7	1.13	1.11	1.15	1.13	1.12	1.06
8	1.28	1.27	1.27	1.26	1.26	1.22
9	1.42	1.41	1.42	1.41	1.42	1.37
10	1.57	1.57	1.57	1.56	1.56	1.57
11	1.73	1.73	1.73	1.72	1.71	1.77
12	1.89	1.89	1.88	1.88	1.89	1.97
13	2.06	2.04	2.04	2.09	2.06	2.15
14	2.20	2.21	2.21	2.21	2.23	2.34
15	2.37	2.36	2.38	2.38	2.38	2.51
16	2.52	2.52	2.53	2.53	2.53	2.67
17	2.66	2.65	2.68	2.67	2.68	2.82
18	2.77	2.74	2.80	2.78	2.78	2.92
19	2.88	2.84	2.92	2.88	2.90	2.97
d_1	-	0.3	0.34	0.22	0.12	1.5
w_1	-	19	19	19	19	5

Figure 4.6: Images of different subjects in different angles and scales and table showing the first feature vector values of the images

Chapter 5

Conclusions and Future Work

Biometrics plays an important role in personal identification. The importance of biometrics in everyday life has been discussed and different biometric technologies are introduced. It has been shown that ear also is a good biometric and is comparable to that of face. Different appraoches for ear recognition were discussed. A simple two-stage geometric approach based on max-line, the longest line that can fit in the ear, has been proposed and is shown to be scale and rotation invariant and the advantage of classifying in two stages has also been discussed. The experimental results have been shown. The accuracy of the approach is shown to be 95%.

The approach is mainly based on the max-line. For the max-line to be found out accurately the outer shape of the ear should be fine. Only such ears were considered for the experiment. The approach should be extended to the ears which are occluded with hair or ear ring. In the approach proposed only one max-line is considered for an image. An extension to the approach would be to use more than one max-lines for each image by changing the slope and the length of the max-line. The images have been acquired without any illumination changes. The approach is to be extended to work in varying conditions.

Bibliography

[1] Francesco Bergadano, Daniele Gunetti, and Claudia Picardi. User authentication through keystroke dynamics. *ACM Trans. Inf. Syst. Secur.*, 5(4):367–397, 2002.

[2] B.Moreno, A.Sanchez, and J.Velez. On the use of outer ear images for personal identification in security applications. In *IEEE International Carnaham Conference on Security Technology*, pages 469–476, 1999.

[3] Alexander M. Bronstein, Michael M. Bronstein, and Ron Kimmel. Three-dimensional face recognition. *Int. J. Comput. Vision*, 64(1):5–30, 2005.

[4] Mark Burge and Wilhelm Burger. Ear biometrics in computer vision. *icpr*, 02:2822, 2000.

[5] J Canny. A computational approach to edge detection. *IEEE Trans. Pattern Anal. Mach. Intell.*, 8(6):679–698, 1986.

[6] Kyong Chang, Kevin W. Bowyer, Sudeep Sarkar, and Barnabas Victor. Comparison and combination of ear and face images in appearance-

based biometrics. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(9):1160–1165, 2003.

[7] Hui Chen and Bir Bhanu. Contour matching for 3d ear recognition. *wacv-motion*, 01:123–128, 2005.

[8] Michal Choras. Ear biometrics based on geometrical feature extraction. *Electronic Letters on Computer Vision and Image Analysis (Journal ELCVIA)*, 5:85–95, 2005.

[9] M. Gifford and N. Edwards. Trial of dynamic signature verification for a real-world identification solution. *BT Technology Journal*, 23(2):259–266, 2005.

[10] Rafael C. Gonzalez and Richard E. Woods. *Digital Image Processing*. Addison-Wesley Publishing Company, 1993.

[11] David J. Hurley, Mark S. Nixon, and John N. Carter. A new force field transform for ear and face recognition. In *ICIP*, 2000.

[12] David J. Hurley, Mark S. Nixon, and John N. Carter. Force field feature extraction for ear biometrics. *Comput. Vis. Image Underst.*, 98(3):491–512, 2005.

[13] A. Iannarelli. *Ear Identification, Forensic Identification Series*. Paramont Publishing Company, 1989.

[14] Anil K. Jain, Salil Prabhakar, and Lin Hong. A multichannel approach to fingerprint classification. *IEEE Trans. Pattern Anal. Mach. Intell.*, 21(4):348–359, 1999.

[15] Jaemin Kim, Seongwon Cho, Jinsu Choi, and II Robert J. Marks. Iris recognition using wavelet features. *J. VLSI Signal Process. Syst.*, 38(2):147–156, 2004.

[16] Xiaomei Liu, Kevin W. Bowyer, and Patrick J. Flynn. Experimental evaluation of iris recognition. In *CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops*, page 158, Washington, DC, USA, 2005. IEEE Computer Society.

[17] Judith A. Markowitz. Voice biometrics. *Commun. ACM*, 43(9):66–73, 2000.

[18] Michael Goh Kah Ong, Tee Connie, Andrew Teoh Beng Jin, and David Ngo Chek Ling. A single-sensor hand geometry and palmprint verification system. In *WBMA '03: Proceedings of the 2003 ACM SIGMM workshop on Biometrics methods and applications*, pages 100–106, New York, NY, USA, 2003. ACM Press.

[19] Sharath Pankanti, Salil Prabhakar, and Anil K. Jain. On the individuality of fingerprints. *IEEE Trans. Pattern Anal. Mach. Intell.*, 24(8):1010–1025, 2002.

[20] K. H. Pun and Y. S. Moon. Recent advances in ear biometrics. *fgr*, 00:164, 2004.

[21] Jonas Richiardi and Andrzej Drygajlo. Gaussian mixture models for on-line signature verification. In *WBMA '03: Proceedings of the 2003*

ACM SIGMM workshop on Biometrics methods and applications, pages 115–122, New York, NY, USA, 2003. ACM Press.

[22] Barnabas Victor, Kevin Bowyer, and Sudeep Sarkar. An evaluation of face and ear biometrics. *icpr*, 01:10429, 2002.

[23] Ping Yan and Kevin W. Bowyer. A fast algorithm for icp-based 3d shape biometrics. *autoid*, 0:213–218, 2005.

[24] Ping Yan and Kevin W. Bowyer. Multi-biometrics 2d and 3d ear recognition. In *AVBPA*, pages 503–512, 2005.

[25] Ping Yan and KevinW. Bowyer. Ear biometrics using 2d and 3d images. In *CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops*, page 121, Washington, DC, USA, 2005. IEEE Computer Society.

[26] Ping Yan and KevinW. Bowyer. Empirical evaluation of advanced ear biometrics. In *CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Workshops*, page 41, Washington, DC, USA, 2005. IEEE Computer Society.

[27] Yossi Zana and Jr Roberto M. Cesar. Face recognition based on polar frequency features. *ACM Trans. Appl. Percept.*, 3(1):62–82, 2006.