On Smartphone Latent Earmarks

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by

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in
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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Cybersecurity Engineering.

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I, Elif ÖZCAN SÖZERİ, declare that this thesis titled, 'On Smartphone Latent Earmarks' and the work presented in it are my own. I confirm that:

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Date: 23 January 2017

"Human can achieve the impossible is not sufficient. Because human can also achieve beyond the impossible."

Nikola Tesla

On Smartphone Latent Earmarks

Elif ÖZCAN SÖZERİ

Abstract

Ear biometric gets attention for more than ten years [3]. There are several studies in the literature. They show that the earmarks are different for every person and comparatively invariant throughout in perpetuity. The earmark has been using in forensic sciences for person recognition for many years. Throughout place of murder inquiries, earmarks are used to find the criminal. At the present times, earmarks are called evidence for the crime scene [51, 52]. Ear biometric recognition technology is recently used for earmark recognition. In this thesis, SIFT algorithm is used in system of the earmark recognition. The acquired data showed that the success rate of the earmark recognition system is 99.72%. Results of this study can be used as a resource for future works. Many ear image databases are available online. So, they are accessible to researchers. On the other hand, there is not any earmark image database available. SIFT algorithm was tested using the earmark image database that created by the researcher. The database includes 912 images belong to 50 individuals who are 29 women and 21 men. For each ear, four images were captured in three sessions by four different smartphones. 800 samples were collected in the first two sessions and 112 samples in the third one. The experimental results stated that latent earmarks on the smartphone can be used for biometric recognition. Latent earmarks on smartphone are becoming visible under good lighting. So, that earmark verification can be performed like fingerprint verification on the smartphone. The success rate of earmark verification varies by different smartphone brands. It is because the materials used on smartphones'screens are different from each other. Also, success rates of earmark verification of a smartphone depend on whether the smartphone has the screen protector or not. The obtained results showed that the iPhone 6 with screen protector has the highest success rate with 99.94% among other smartphones. In future, increasing the number of people can enhance this study. People from different geographies can be used to investigate the effect of genetic factors on ears. The changes can be observed more clearly when the ear recording periods are longer.

Keywords: Engineering, Experimental biometric, Ear biometric, Earmark biometric, SIFT, Identification, Verification, Smartphone, Earmark, Earprint, Forensic evidence.

Akıllı Telefonlardaki Görünmez Kulak İzi

Elif ÖZCAN SÖZERİ

Öz

Kulak biyometrisi on yılı aşkın bir süredir dikkatleri çekiyor [3]. Literaturde Kulak biyometrisi ile ilgili birçok çalışma vardır. Kulak adli bilimler alanında uzun yıllar kimlik tanımlama için kullanılmıştır. Olay yeri incelemelerinde geçerli parmak izinin olmadığı durumlarda kulak izleri kimlik tespiti ve delil için sıklıkla kullanılır [51, 52]. Kulak biyometrisi tanımlama teknolojisi, biyometri tanımlama alanında yeni bir konudur. Bu tezde SIFT algoritmasına dayanan bir kulak biyometrisi tanımlama sistemi sunulmuştur. SIFT algoritmasında kulak izlerinden çıkarılan özellikler, oluşturulan benzersiz şablonla birlikte hesaplanır. Bu şablon nesneye ait özellikler içerir. Elde edilen sonuçlar, önerilen sistemin doğru tanımlama oranını %99,72'ye yükselttiğini göstermektedir. Yakın gelecekte, kulak izlerine ait bu çalışmalar başka çalışmalar için yol gösterici olacaktır. Herkesin kullanımına açık hazır kulak fotoğrafları içeren veritabanı mevcuttur, ancak kulak izleri içeren hazır veritabanı bulunmamaktadır. Bu yüzden SIFT algoritması, oluşturulan kulak izi veritabanında test edilmiştir. Kulak izi fotoğrafı veritabanı 912 fotoğraftan oluşur. Her kulak için 4 ayrı fotoğraf üç ayrı oturumda, dört farklı markaya ait telefonla alınmıştır. Birinci ve ikinci oturumda 800 örnek, üçüncüsünde 112 örnek toplanmıştır. Bu veritabanındaki fotoğraflar, 29 kadın ve 21 erkek olmak üzere toplam 50 kişiye ait fotoğrafları içermektedir. Deney sonuçları, akıllı telefondaki gizli kulak izlerinin biyometrik tanımlama için kullanılabileceğini göstermektedir. Akıllı telefonların üzerindeki gizli kulak izleri iyi bir aydınlatma ile görünür hale gelmektedir. Böylece, akıllı telefon yüzeyindeki parmak izi doğrulamasına benzer şekilde kulak izi doğrulaması da yapılabilir. Kulak izi doğrulama başarı oranı akıllı telefonlardaki markalara göre değişmektedir. Çünkü akıllı telefonlarda kullanılan metaryaller birbirinden farklıdır. Aynı marka akıllı telefonda kulak izi doğrulama başarı oranının farklıdır çünkü birisinde ekran koruyucusu vardır, diğerinde yoktur. Elde edilen sonuçlarda ekran koruyuculu iPhone 6 marka akıllı telefonun %99,94 başarı oranıyla en yüksek kulak izi doğrulama başarısına sahiptir. Gelecekte bu çalışmanın geliştirilmesi için kulak izi alınan birey sayısı artırılabilir. Farklı coğrafyalardaki insanlar, genetik faktörlerin kulak izleri üzerindeki etkilerini araştırmak için kullanılabilir. Kulak izi alma periyotları daha uzun olduğunda kulaktaki değişimler daha net görülebilir.

Anahtar Sözcükler: Mühendislik, Deneysel biyometri, Kulak biyometrisi, Kulak izi biyometrisi, SIFT, Tanımlama, Doğrulama, Akıllı telefon, Kulak izi, Adli delil.

I dedicate this study to my beloved family and my husband.

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Abbreviations

SIFT	**S**cale **I**nvariant **F**eature **T**ransform
LBP	**L**ocal **B**inary **P**atterns
PCA	**P**rincipal **C**omponent **A**nalysis
ICP	**I**terative **C**losest **P**oint
ICA	**I**ndependent **C**omponent **A**nalysis
DoG	**D**ifference of **G**aussian
ROC	**R**eceiver **O**perating **C**haracteristic
EER	**E**qual **E**rror **R**ate
FAR	**F**alse **A**cceptance **R**ate
FRR	**F**alse **R**ejection **R**ate
TSR	**T**otal **S**uccess **R**ate
SWGR	**S**um of **W**eighted **G**lobal **R**atio
SWGA	**S**um **W**eight **G**athering **A**lgorithm
SFFS	**S**equential **F**loating **F**orward **S**election
NIS	**N**aturalization **I**mmigration **S**ervice
LLE	**L**ocally **L**inear **E**mbedding
FFT	**F**orce **F**ield **T**ransformation
IRT	**I**mage **R**ay **T**ransform
G	**G**allery
P	**P**robe

Chapter 1

Introduction

1.1 Biometric Systems

Biometric word is formed from the combination of life and measure [1]. Person's physiological and behavioral characteristics are automatically identified thanks to biometrics [1]. These characteristics are unique, individual and can be used in the identification and verification [5]. Ears, hand geometry, voice tone, DNA, signature dynamics, fingerprints, iris and vein patterns, gait, odor and face detection are the types of biometrics [1]. Most of systems are only used passwords,captcha and they are stolen by hackers [5]. Major advantages of biometric characteristics are that these features can not be forgotten, lost and made too unpredictable. Nowadays biometric plays an important role in verification and identification individuals in security systems. Biometrics can be either obviously seen. Also it helps recognize the person [12]. In figure 1.1 some of the biometric properties are shown.

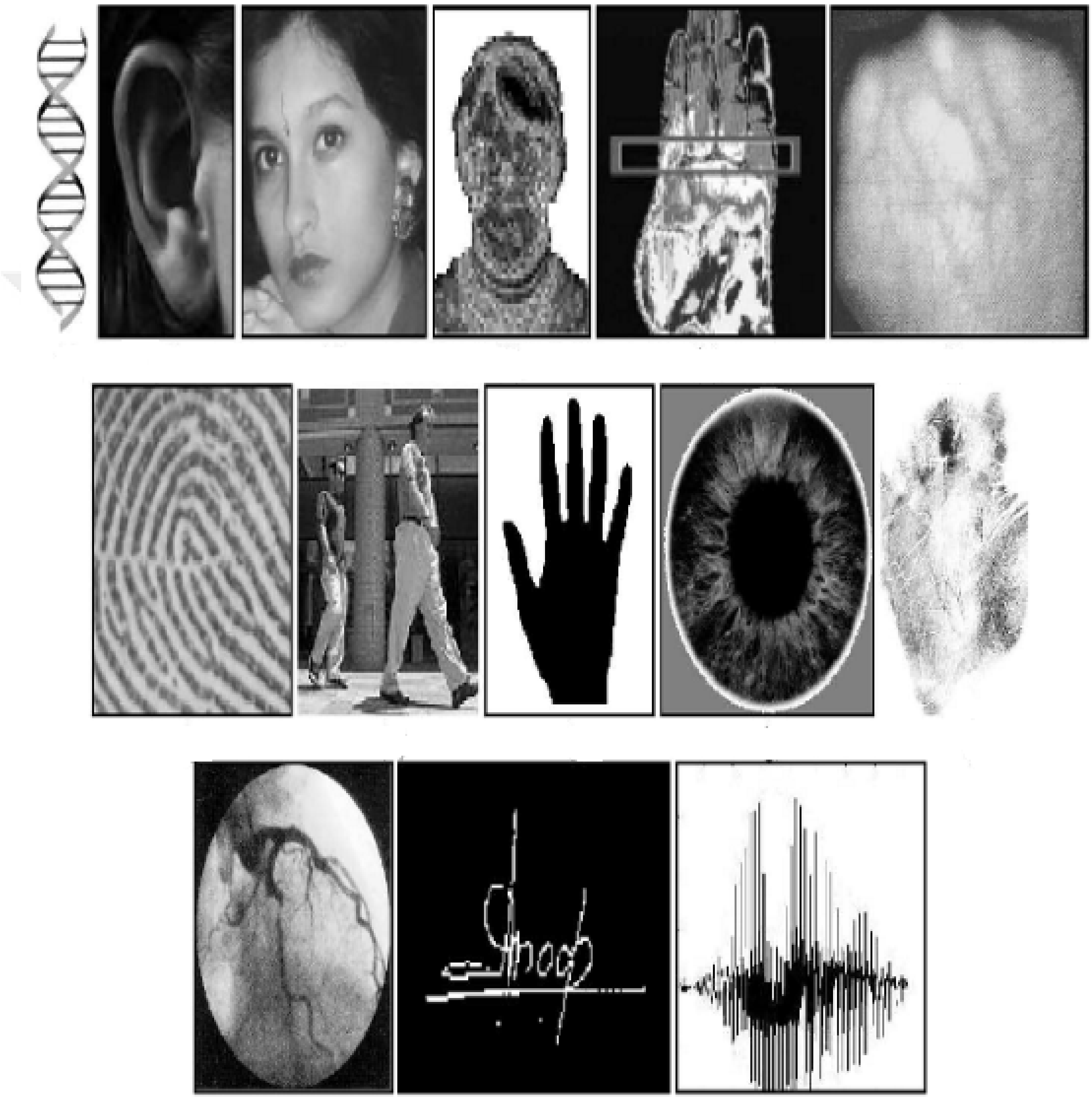


FIGURE 1.1: Biometric patterns [8].

Many applications have authentication and authorization in everyday life [1]. Biometric recognizes an individual basing on characteristics needed for automated method [1]. Biometrics shows improvements in such aspects as security, data integrity, fault tolerance, system recovery [1]. Biometrics has included a reliable solution for protecting identity and recognition of matchless and stable properties, also it is being defined for authentication techniques in Figure 1.2 [1].

- Identification: It contains biometric features [1]. The system compares the acquired features with database data. Matcher using a 1: N solution for identification [7].
- Verification: Verification either confirms or denies a individual's demanded feature [1]. A biometric feature is being accepted.Verification is using a 1:1 matching solution [7].

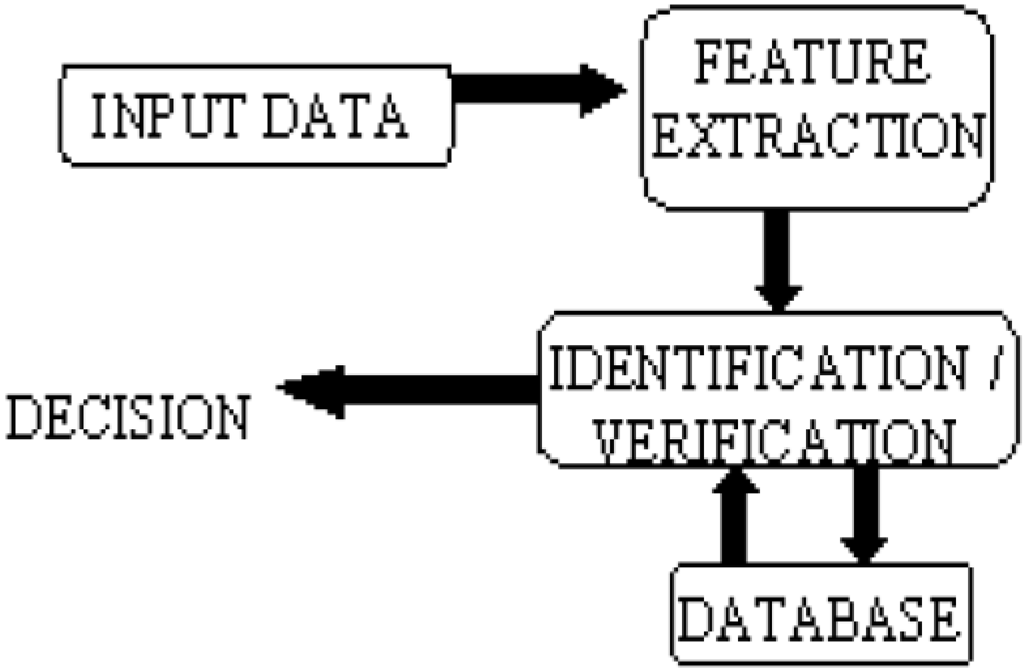


FIGURE 1.2: Authentication process [1].

Biometrics system has seven parameters such as: universality, permanence, performance, collectability, acceptability, distinctiveness and circumvention. Human biometric traits were compared by seven parameters in the Table 1 [8].

TABLE 1.1: Biometric features [8].

Biometric Trait	Univers-ality	Distinctive-ness	Perma-nence	Collect-ability	Perform-ance	Accept-ability	Circum-vention
Ear	Medium	Medium	High	Medium	Medium	High	Medium
Face	High	Low	Medium	High	Low	High	High
Fingerprint	Medium	High	High	Medium	High	Medium	Medium
DNA	High	High	High	Low	High	Low	Low
Retina	High	High	Medium	Low	High	Low	Low
Iris	High	High	High	Medium	High	Low	Low
Signature	Low	Low	Low	High	Low	High	High
Keystroke	Low	Low	Low	Medium	Low	Medium	Medium
Voice	Medium	Low	Low	Medium	Low	High	High

A biometrics system can be defined as a pattern recognition system which works by obtaining biometric feature from a person, take out a properties from the acquired information, and matching that identity with the database information [8].

A biometrics system may work on verification process or identification process, depending on the application context [6]. The enrollment process is the first step of any biometric system also it is being used for registration a novel individual in the system [6].

Due to the verification process the main aim is to avoid unauthorized individuals and refuses many individual from same certificate [6, 9].

In the identification process, the system identifies the person by seeking biometric template of entire the people in the system database for pair. Identification aim is to avoid a one individual from using many certificates [6].

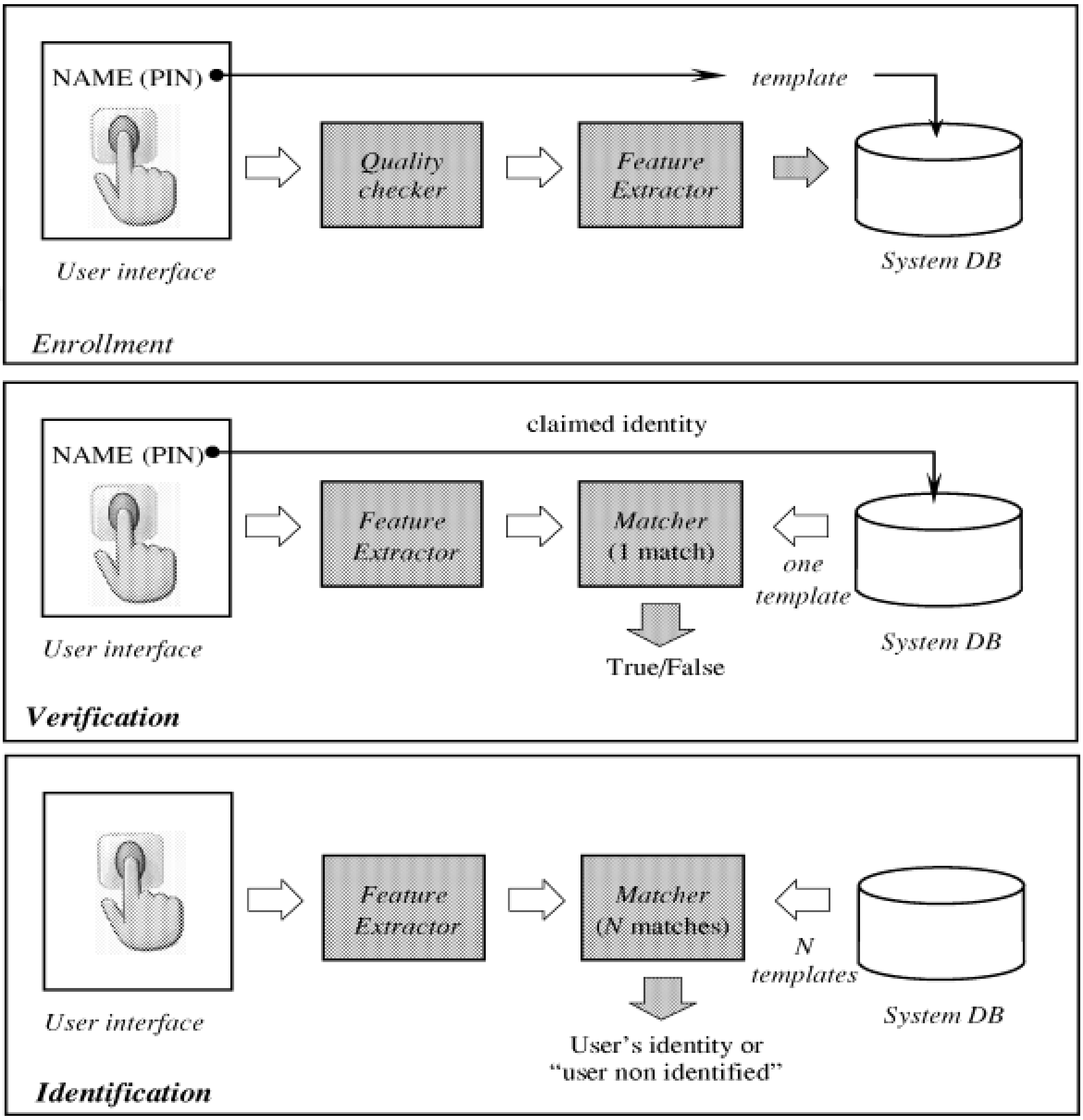


FIGURE 1.3: Block diagram of the enrollment, verification, and identification tasks [8].

1.2 Ear Biometrics

Public safety and national security generally using biometric techniques, as the most secure and accurate authentication applications. Physical biometric features like fingerprints, face, hand geometry have admitted deep concern. Vascular Scar, fingerprint, voice and retina are usually being used for identification and verification. However the usage of face in biometrics is easier than others. Even if you do not know the other biometric information of the person, you can still get face information. An ear biometric is more useful in this regard. Nevertheless, the face is not still as correct and suitable as required for that case because of the lighting changes, mimic changes, makeup or eye glasses.

FIGURE 1.4: Standard of the biometric image [20].

Ear images method is the same as face images. Many investigators have argued that the ear is inimitable. Many investigators have worked on 2D ear model [13, 14, 15, 16, 17]. Some investigators have worked on 3D ear model [18, 19]. Actually, the ear was used as biometric unofficially. For instance, the INS has necessitate that the right ear must be obvious, shown in Figure 1.4 [20].

The ear is matchless for every human. However, it may show slight changes until adulthood [3]. Some studies have been done about the inimitableness of the ear shape [3] and obtain observational supporting evidence. The research says that the variance in age range which is recognizable throughout 8 years old and over 70 years old. In addition, ear growth in this age range is linear. After age 70, the ear continues to grow [13] and stretch rate is not linear because of gravity. Ear identification is often used because of thestability and predictable changes of the ear [18, 21, 13, 14, 15, 16, 29,17].

At the present times, earmarks are called evidence for the crime scene [51, 52]. The ear does not change over time [13]. Earmark satisfies entire the qualities such as inimitableness, generality, efficiency etc [11]. The ear shape has standard parts same as other biometric types. In figure 1.5 indicates the standard features of ear anatomy [10]. Ear shape is significantly coherent and stable. The external ear is very significant for ear biometrics. The system of ear biometric includes detection and recognition parts.

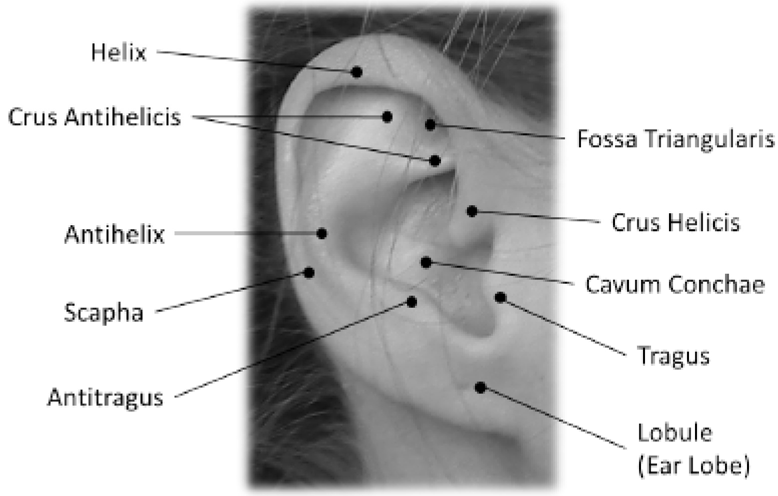


Figure 1.5: The ear anatomy [10].

After measurements of a lot ear photographs of identical twins, it was determined that two ears are different from each other [3]. Ear-based recognition is taking attention not only because of being non-invasive but also due to the fact that it is not being affected by such factors as psychology and cosmetics as the face does. According to the studies, magnitude of decisiveness value of the ear is greater than one of the face [4]. Unlike the face, the ear shape may not be symmetrical, which in turn means that the both ears of every person is different. The advantages of ear biometrics are listed following [4]:

- According to medical studies ear shape is found to be stable and constant during the human life.
- The ear has passive biometrics case. Ears features can be captured from a distance.
- The ear can be obtained with less effort. Because the area of the ear is bigger than fingerprint, retina etc.
- The ear has uniform colour distribution.
- The ear is unaffected by eye glasses and makeup.
- Handling background of the ear is not a tough subject.

The ear can be used in an independent mode for recognition or it can be integrated with the multi-biometrics techniques such as face recognition. Ear biometrics can be used for access control applications and government security such as visa/passport programs. According to individuals, the ear biometrics is less intense than fingerprinting. The ear biometrics systems have no hygiene problems because there is no need to touch any devices.

Face biometrics is less secure than ear biometrics, mostly so it is difficult to establish a relationship between the ear and the earmark. Thus individuals are not able to recognize own earmarks. For this reason, the earmark databases are more secure than others.

People are hindered in description of earmarks. The main reason of ear biometrics based on computer vision systems. Data of the ear is obtained with these systems.

Chapter 2

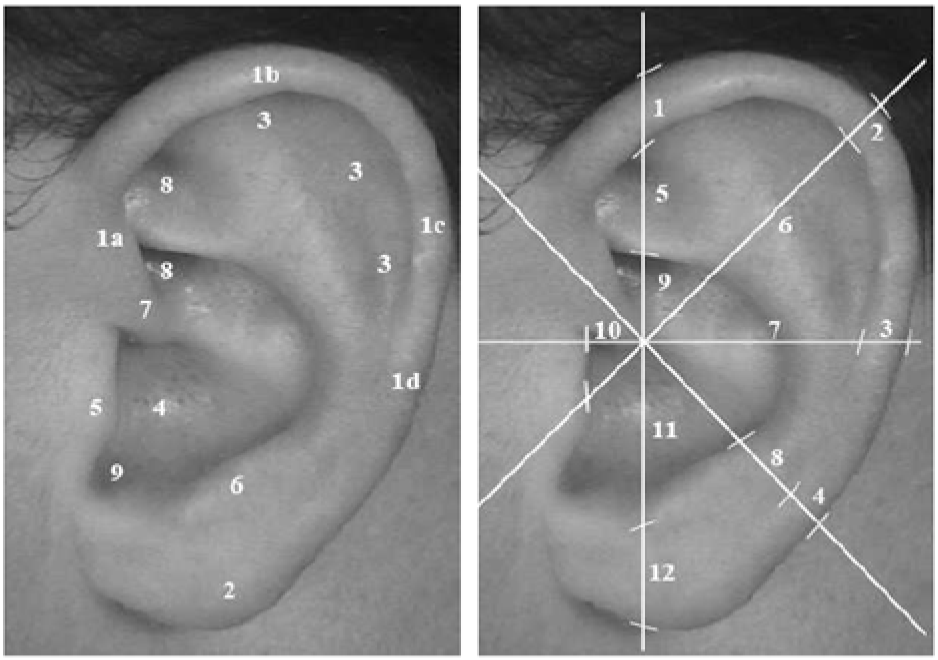
Literature Review

As previously mentioned, A lot of researchers are working on the ear biometrics. There are several studies showing that the ear is different from each person. furthermore, two studies [13, 21] are supported by evidence. Thus the earmarks are usual evidence in many real criminal inquiries [22].

In 1906, Imhofer did a study. In this study, just 4 features were required to recognize approximately 500 ears [23].

In 1989, Iannarelli did the notable work [3]. In this work, more than 10.000 ears were analyzed and it has been found that the ears, were different from each other. Iannarelli developed an anthropometric technique which uses 12 measurements for the "Iannarelli System" ear identification.

When the ear reaches the proper position, the ear image should be covered inside the borders. The borders should be cautiously set till the inclined guide line which is parallel to the tragus flesh line. The inclined line must merely intersect the tragus.



(a) Anatomy (b) 12 Measurements used in 'Iannarelli System"

FIGURE 2.1: The Iannarelli system [37].

Firstly, the image is fully lined up with the inclined guide line. Then the image is placed. The expert should be focalize the image in appropriate diamension. The short vertical guide line goals to increase appropriate dimension for classification [3]. The ear features allow to develop for tool of identification[18, 21, 13, 14, 15, 3, 17].

TABLE 2.1: Ear biometric researchs [20].

Reference	Data Used	Dataset Size	Time Lapse	Number of G/P*	Method Applied	Earrings/Occlu.	Reported Perfor.
Chen & Bhanu [19]	3D	30x2	Same Day	1/1	ICP	No	93%
Hurley & Nixon [16]	2D	63x4	5 Month	1/1	PCA	No	99.2%
Moreno et al. [24]	2D	28x6	Different Days	1/1	Neural Network	Not mention	93%
Yuizono et al. [25]	2D	110x6	Same Day	3/3	Geometric Search	Not mention	100%
Chang et al. [14]	2D	88x2	15 Month	1/1	PCA	No	73%
Choras [29]	2D	N/A	Same Day	N/A	Feature based	No	100%

Moreno et al. [24] was used three neural network paradigm for ear recognition. In this experiment dataset of 28 individual were used. The best recognition rate of the three approaches was 93%.

Victor [17] and Chang [14] have observed PCA with two-dimensional density ear photos. The performance of the ear biometry was compared with the performance of the face biometry in studies and different results were obtained.

Yuizono et al. [25] studied a identification system for subjects of the ear by hereditary research. As a result of the research, they noticed that the identification ratio for the recorded individual was almost 100%, and the denial ratio for the unrecognized individual was 100%.

Bhanu and Chen obtained three-dimensional biometric definitions in their work. Surface identifiers [18] are used as methods.They have achieved 100% success rate in the system. Another work by Bhanu and Chen [19] applied a two-step ICP algorithm for three-dimensional objects. The success rate of the system was approximately 6%. The objects were not automatically cropped in two surveys [26].

Hurley et al. [15] improved new property extraction method via FFT. Every photo is showed by an intensive feature vector. The study has powerful technique for extract properties of the two-dimensional ear. The researchers have used the force field technique in the next phase of the research. [16]. Their gallery includes , 252 images belong to 63 individuals. An ear classification ratio is 99.2%.

Chora's [29] has investigated the probability of utilization in ear biometrics. The report shows the two-dimensional ear set, and present an ear identification approach depend on geometric property extraction. The researcher worked on the "easy" ear photographs for a errorless ear identification system. 'Easy' ear photographs have been shot at high quality. Also, the photos are cropped and the environmental conditions are stable. The experiment has not detail reported.

Pun and Moon [30] performed small-scale literature comparison in their work. According to experimental data in the literature, they research structures of five methods [18, 21, 14, 15, 25]. In Table 2.1, works in the literature are compared according to some parameters.

In research, first examines different procedures of two-dimensional and three-dimensional ear recognition . This study showed that three-dimensional ear recognition using ICP is better. Actuarially, significantly better is the two-dimensional "eigen-ear" result [14]. Therefore three dimensional ear recognition methods are stronger than two dimensional ear recognition methods.

Only two researches [18, 19] are interested in three-dimensional ear shape biometrics. They include the largest gallery with 110 individuals [25]. This study might interest because of earrings. This is the only study that entirely perceives the ear image from a profile outlook.

Lastly, literature review table summary Table 2.2 is shown. It includes reference names, databases, methods and success rates.

Table 2.2: Literature review table.

Reference Name	Database	Methods	Success Rate
P. Yan [20]	415 people	PCA(2D) ICP(3D)	97.6%
H. Azadi [32]	7364 sample 1229 people 9left ,9 right images	SIFT,CSS,RANSAC	EER % 2.22
A. Mathur [33]	50 sample5people	PCA	53%
L.Yuan, Z. Mu,& Z. Xu [34]	PCA197, ND Human ID database, ICP 60	PCA(2D) ICP(3D)	PCA %71,2 ICP %93,3
B.Bhanu, H.Chen [35]	UCR dataset155 people 902images, UND dataset 302 people 604images	Helix/antihelix, LSP	Performanc e two datasets 5.8%-2.4%
A.Pug, C. Busch [36]	UND collections,85 ear images from 17 subjects	PCA	Rank-1 40%
T.V.Kandgaonkar, R.S. Mente, A. R. Shinde & S.D.Raut [37]	Open db	Geometry of curves of Ear in 2D,Fourier Transformation,Wavelet Transformation,Gabor Filters, SIFT,3D Ear	1)FRR between 0 to 9.6%
J. B. Jawale, Smt. A. S. Bhalchandra [38]	25 people 21Subjet	Ear Feature Vector Extraction	85%
N.Jamil, A. Almisreb, A. A. Halin [39]	50 subjects	HammingDistance,Gabor	92.66%
D. J. Hurley, B. Arbab-Zavar, M. S. Nixon [40]	ICP 1386,PCA168	PCA, ICP	PCA 97.8%
F.Khursheed, A.H. Mir [41]	IIT Delhi 363 images121 people	Auto Regressive Modelling	99%
M. Choraś [29]	240 images	PCA	
D.Singh, S.K.Singh [42]	XM2VTS 252 images	Force Field Transformation BasedTechniques,Geometric Features Based Techniques	99.6%
L.Nanni, A.Lumini [43]	464 Ears 114 users The University of Notre Dame in Fall dataset	SwGR,SwGA,PCA,ICA,LEM, SFFS	RANK-1 80%

Chapter 3

Ear Marks Procedure,Algorithm and Implementation

3.1 2D Ear Recognition Methods

Ear biometrics has attracted attention in recent years [3]. Earmark is used as evidence by forensic area [51, 52]. According to other types of biometry, the ear has some benefits for individual identification. [49, 50]. The Iannarelli system pioneered ear biometry systems. During the study, many ear identification methods have been recommended by researchers [30, 53]. Two dimensional ear recognition methods are described below.

3.1.1 Holistic Method

FFT is used for the holistic method [15, 58]. The exposure constant is used in FFT [54]. Kumar and Wu [55] studied an ear identification method. In addition, log-Gabor filters were used while the system was being developed. Abate et al. [56] used fourier identifiers in their work. Wang et al. [57] used various property vector in their studies.

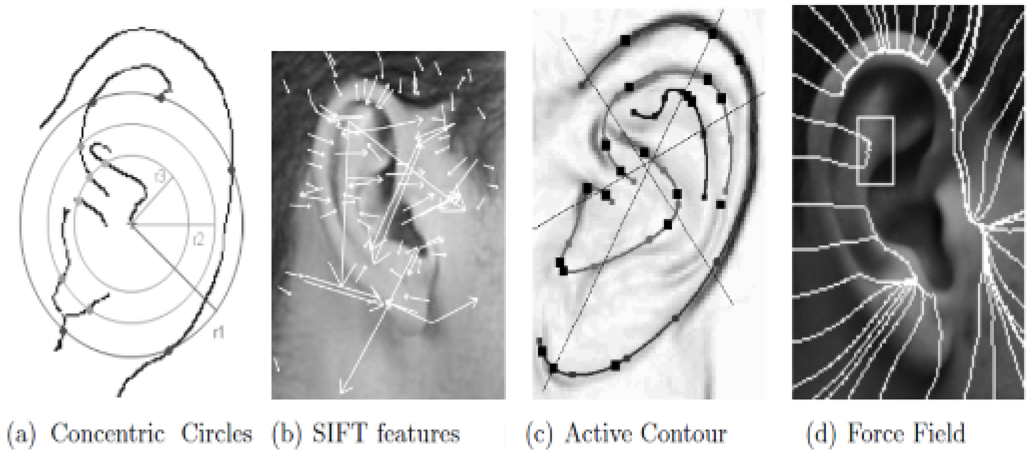


FIGURE 3.1: Samples of feature extraction [36].

3.1.2 Local Method

Researchers have studied about the geometry of ear [29, 59]. Bastard et al. are processed different images of the same object with the SIFT algorithm. Also LBP was used for property extraction at pixel level. Guo et al. [62] found LBP distribution at pixel level in objects. Wang and Yan [63] diminished the size of the property vector using the linear discriminant method.

3.1.3 Hybrid Method

Liu et al. [64] associated images of ears from different angles in their study. Yuan and Mu, [65] and Youdong and Yunde [66] have concentrated on extracting contours of ear from their work.

3.1.4 Statistical Method

Zhang and Mu, [67] conducted works on the impressiveness of statistical methods in combination with classifiers. Xie and MU, [68] committed and developed LLE code for increasing the size of property. Compressed detection is used in the common classification code [69]. Researchers have concentrated on ear biometry methods [36, 70]. However, the seacrh of the time series modeling was ignored.

3.2 Algorithms

There are different methods defined in [45] of recognizing ears. Iannarelli approach is ordered like that:

- It is the basis for ear recognition systems.
- It describes 12 specific areas on two-dimensional ear subject.
- Measurements depend on a normalized ear object.
- Classification: Based on the ear shape as watched by the naked eye e.g., round, triangle, rectangle and oval.

Voronoi diagrams:

- It gives idea about the problem of locating structural points.
- It includes some process such as: acquiring, localizing, extracting edges and curves, graph modeling.

Compression networks:

- Because of the compression network classifier, ear subjects allow the use of property extraction.
- The system utilizes neural networks for biometric identification.

FFT:

- This algorithm uses physical rules such that instance every particle has the strength of attraction.
- Identification of acoustic ear biometrics:
  - The pattern of the ear is utilized.
  - Analysis is performed by sending and receiving signals to the ears.
  - The received signal forms the basis of the ear signature.

PCA :

- Algorithm can compare the changes on the subject.
- Algorithm is implemented by ear or face feature.

IRT :

- A comparatively latest work which has 99.65% success rate.
- Algorithm presents ear features using a ray-producing algorithm.

Modified Snake algorithm:

- It defines the "triangular fossa" shape.
- Still in research stage.

SIFT :

- Algorithm is popular approach that provides a high pattern recognition performance.
- Researchers have suggested the SIFT algorithm [46]. It is also recommended to use CCD [47].

Ear Biometrics [34] advantages:

- Powerful structure protected during the lifetime of the person.
- Unlike facial features, ear structure is stable.
- The dimension of the outcome subject is small under similar resolution. So, it is an added advantage when using a portable device like a cellphone.
- Can be used in negative identification systems and latent operations.

3.2.1 SIFT

SIFT is an algorithm introduced by Lowe [46] that takes an image, detects keypoints and computes its descriptors. These are constant to scale, rotation and translation of the image.

Meijerman et al. [48] used SIFT features to automatically match earmarks. Their method contains the following steps: image preprocessing to resample the images and applyes filter, keypoint detection using the SIFT algorithm of Lowe, keypoint matching defined as the minimum DoG in the SIFT property set [48].

The SIFT algorithm converts subject data into constant locations. Creation of subject property sets includes the below steps [46, 60]:

3.2.1.1 Scale-Space Extrema Detection

This part, defines whole measures and subject positions. The constant points are found using the DoG .

According to the formula 1: the L(x, y, σ) is a sample area function that can be scaled for an image and the G(x, y, σ) is the DoG function that scales to the input image I(x, y).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

where, σ is the scale of blurring. The 2D Gaussian kernel is given by Eq. (2).

$$G(x, y, \sigma) = \frac{1}{2\Pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (2)$$

Lowe [15] uses the D(x, y, σ) for keypoint position assignments. According to the formulas below, the scale is divided into two different divisions by k constants.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \quad (3)$$

$$= L(x, y, K\sigma) - L(x, y, \sigma)) \quad (4)$$

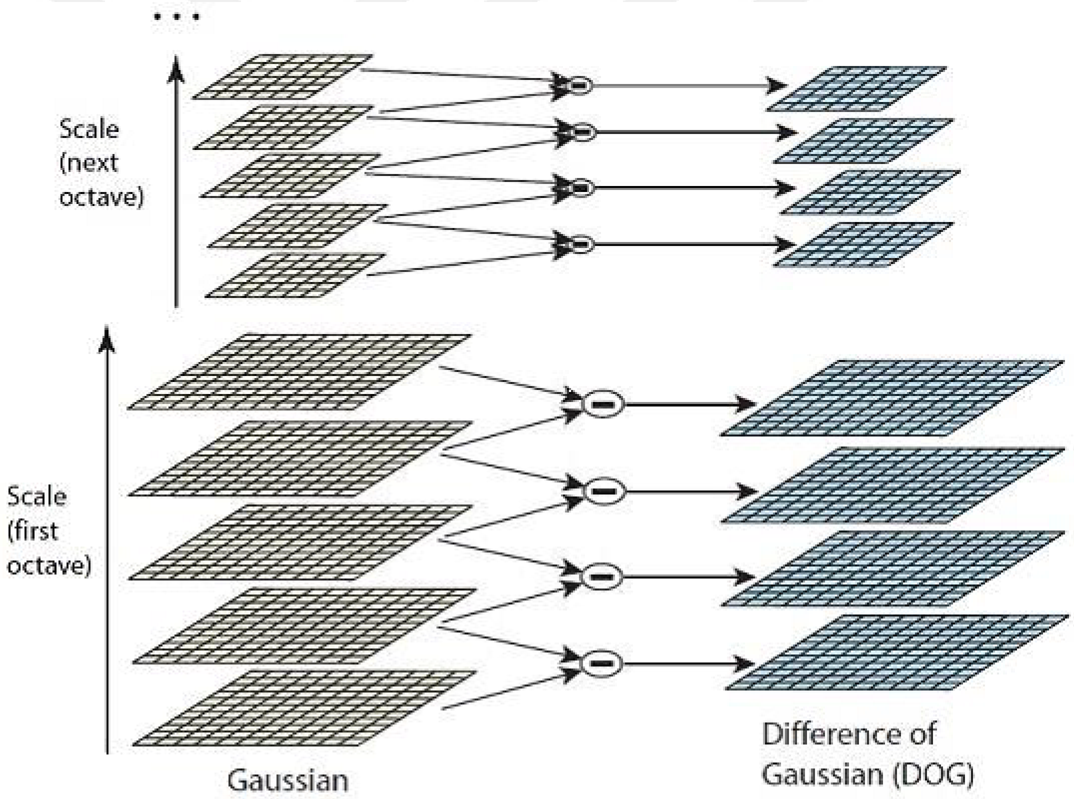


FIGURE 3.2: In the left Gaussian pyramid. On the right Difference of Gaussian (DoG) pyramid [32].

An effective method for the function D(x, y,σ) is shown in Figure 3.2. The intertwined subjects are classification by octave. Each octave is separated by an integer such as k= $2^{\frac{1}{3}}$.

3.2.1.2 Extreme Detection

In extreme detection, extreme points are defined in the DoG pyramid. Each pixel is compared with eight neighbors in the DoG for extreme detection. Subpixel extreme is described by the Taylor enlargement of the image just around the keypoint in the (Figure 3.3).

$$D(\mathbf{x}) = D + \frac{\partial D^T}{\partial \mathbf{x}}\mathbf{x} + \frac{1}{2}\mathbf{x}^\mathbf{T}\frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$

If the function has a zero derivative, the actual extreme point is found.

$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1}\frac{\partial D}{\partial \mathbf{x}}.$$

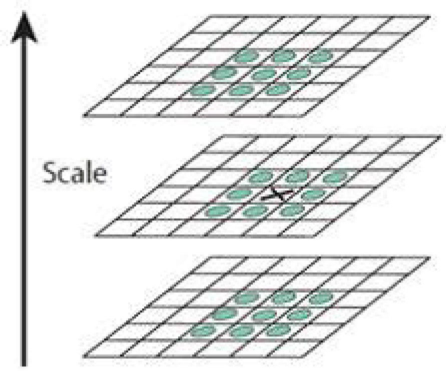


FIGURE 3.3: An extreme is detected as a minimum or maximum value between all its neighbours in DoG scale [32].

3.2.1.3 Keypoints Elimination

Some keypoints created in the previous step lie throughout an edges. If features of keypoint are not available, they will be eliminated [46]. The most extreme keypoint in the DoG image is calculated as follows:

$$D(\hat{\mathbf{x}}) = D + \frac{1}{2}\frac{\partial D^T}{\partial \mathbf{x}}\hat{\mathbf{x}}.$$

The values in the DoG image must be greater than the threshold, otherwise they are rejected. According to the matrix calculation below, they should be eliminated from the keypoint list.

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$$\frac{D_{xx} + D_{yy}}{D_{xx}D_{yy} - (D_{xy})^2} < \frac{(r+1)^2}{r} \qquad (1)$$

So if inequality (1) fails, the keypoint is rejected.

3.2.1.4 Orientation Assignment

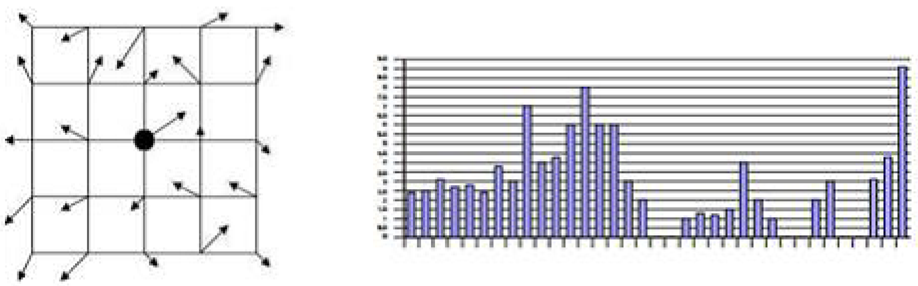


FIGURE 3.4: An orientation assignment [32].

Coherent orientation is defined for every keypoint position. Also, each feature has the assigned orientation, scale and location. So, it is proved invariance to these transformations.

In this stage, orientations are defined as keypoint which is depend on gradient ways. An image sample L(x,y) is image sample. The gradient is calculated by the formula below:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\theta(x,y) = \arctan((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$

Size and orientation are calculated for each pixel at the keypoint. Thus a histogram as illustrated in Figure 3.4. is genereted [46]. The histogram will have a top at some points. The tops in this histogram come across heavy orientations. If there are more than one top, a new keypoint is created with the same position like the original keypoint. However, its orientation is same by additional top because orientation should be split by various keypoints.

This is key phase in achieving invariance to image rotation. The position of the keypoints is still unchanged. In Figure 3.4, keypoints are indicated as arrows. The length of the arrows indicates the magnitude of the contrast at the keypoints.

3.2.1.5 Keypoint Descriptor

In this step, an each keypoint descriptor vector is calculated so that the descriptor is highly distinctive. Then, a 16×16 window is calculated around the keypoints [46] which are disunited to 16 subblocks. Inside of subbloks, gradient magnitudes are computed. The magnitudes are weighted by half the width of the sub-blocks. This process is represened in the Figure 3.5.

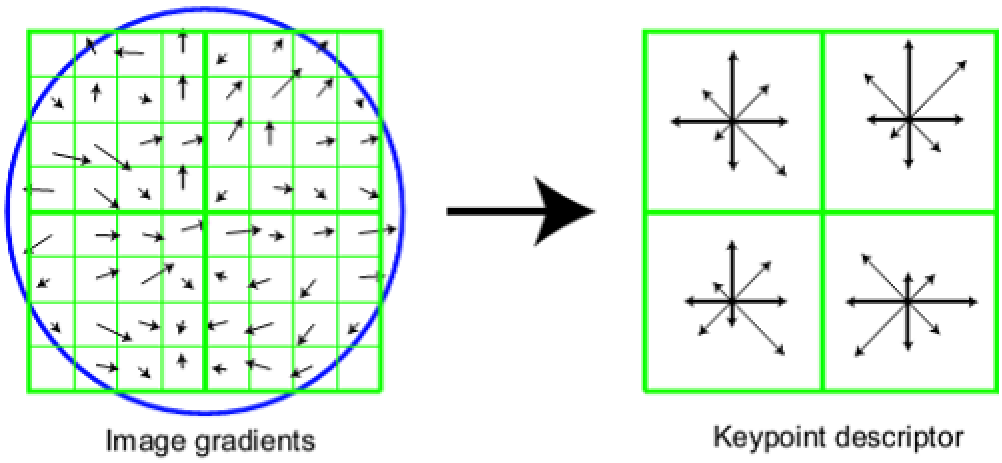


FIGURE 3.5: Keypoint descriptor [32].

3.3 Earmarks Taking Procedure

Earmarks taking procedure can be divided into 6 main parts such as: mobile phone selection, camera and background selection, lighting selection, determination of taking on mobile phone earmarks order, photograph naming rule, photograph storage rule.

FIGURE 3.6: Earmarks taking system.

3.3.1 Mobile Phone Selection

In the nowadays market the most widely used brands are Apple and Samsung [1]. Total of 4 mobile phones are used for taking an earmarks. Two phones of each brand were used, one of each with and without screen protector. iPhone 6 Plus has no screen protector. iPhone 6 has screen protector. Samsung Galaxy S3 Mini has screen protector. Samsung Galaxy Wgt-18150 has no screen protector. Mobile phones were selected due to the effect of screen protector on taking earmarks.

3.3.2 Camera and Background Selection

The photo shoot was done using the brand Nikon Coolpix L330 camera. Also tripod used for stabilizing the camera. The black fine cardboards with size of $60cm \times 70cm$. were used as background to absorb light. Also black background was used because it is better light absorbed [44].

3.3.3 Lighting Selection

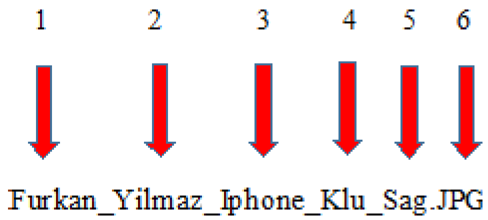
Lighting was provided with two floor lamps. Brand of floor lamps are Lambamina. Floor lamp from Philips tornado cool daylight 145 watt brand bulb was installed. High-powered light was selected to absorb the environmental lights.

3.3.4 Determination of Taking on Mobile Phone Marks Order

Two floor lights have been opened. The place of the phones were determined on the background. Tripod set to 80 cm height from the ground and ninety degree angle with camera. Labels which writing the people names were placed on the background. Firstly, iPhone 6 without screen protector was set on thirty-degree angle with the floor. Phone was removed from the ear and taken to the marked place. Cameras was set on the automatic shooting mode with 10 minutes period. Doing so tremor and slip have been prevented and provided the best pictures to be captured. The same procedure applies to iPhone 6 with screen protector, Samsung Galaxy S3 Mini without screen protector, Samsung Galaxy S3 Mini with screen protector, Samsung Galaxy Wgt-1815 without screen protector and Samsung Galaxy Wgt-1815 with screen protector respectively.

3.3.5 Photograph Naming Rule

The photographs are named as follows;



1. Name
2. Surname
3. Mobile phone brand
4. Mobile phone screen protector
5. Ear side
6. File extension type

3.3.6 Photograph Storage Rule

Photos are stored as indexed in the folder.

Chapter 4

The Proposed Approach

As a shown in Figure 4.1, the proposed approach has 4 stages. These are; ear preprocessing (includes localization of ear and enhancement of ear), feature extraction of ear, feature concatenation of ear, matching of ear.

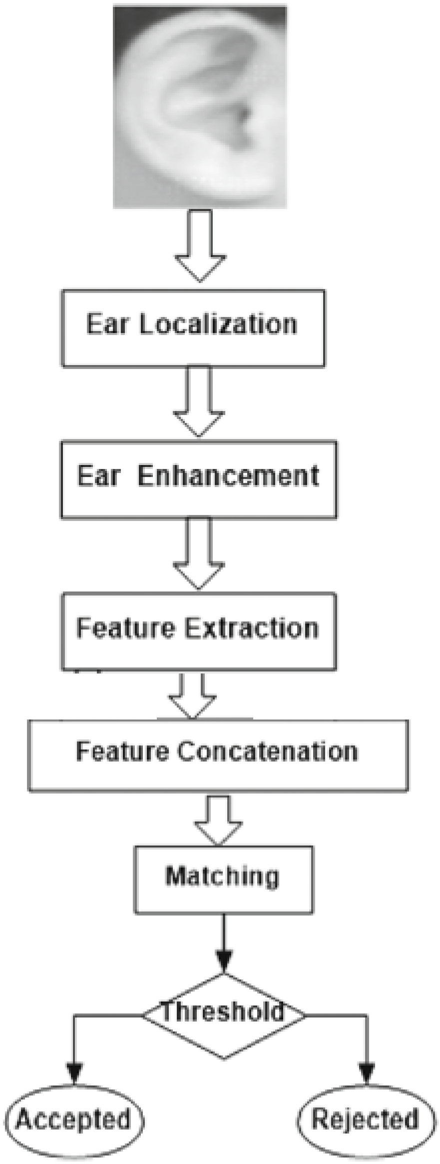


FIGURE 4.1: Architecture of proposed ear biometric system [71].

4.1 Pre-processing of Images

In this preprocessing of images phase, the earmark images were trimmed by hand. The entire preprocessing operation is represented in Figure 4.2, and Figure 4.3.

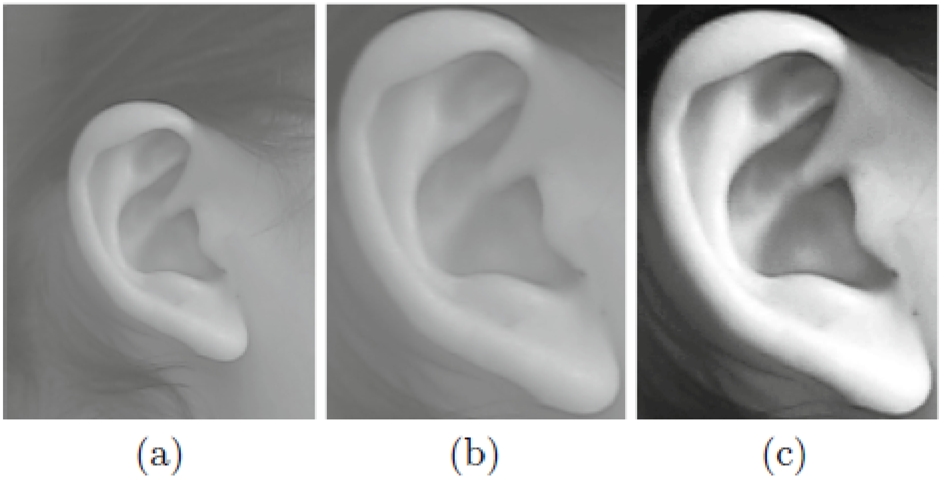


Figure 4.2: The chain of ear preprocessing [71].

Figure 4.3: Illustration of the pre-processing of images [32].

4.2 Feature Extraction

SIFT technique [46] was used to extract the property. They are constant to scale, rotation and affine transformation seen in section 3. Figure 4.4 presents the detected keypoints of ear respectively.

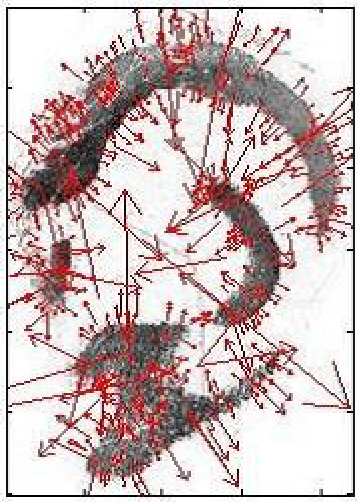


FIGURE 4.4: Illustration of ear feature extraction using SIFT [32].

4.3 Matching

In this stage, the input ear images with detected keypoints are processed. Afterward they are contrasted with the assembled templates along the enrollment stage. The pairing of each keypoint is obtained finding by candidate properties. Euclidean distance is used for mapping. According to the mappinging score, the individual is accepted or rejected in the system. In Figure 4.5 presents the mapping keypoints of earmark images from the same individual. In Figure 4.6 shows the matching keypoints including outliers (left) and matched keypoints including inliers only (right).

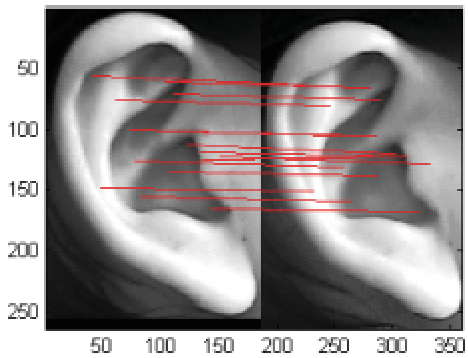


FIGURE 4.5: Matching of keypoints [71].

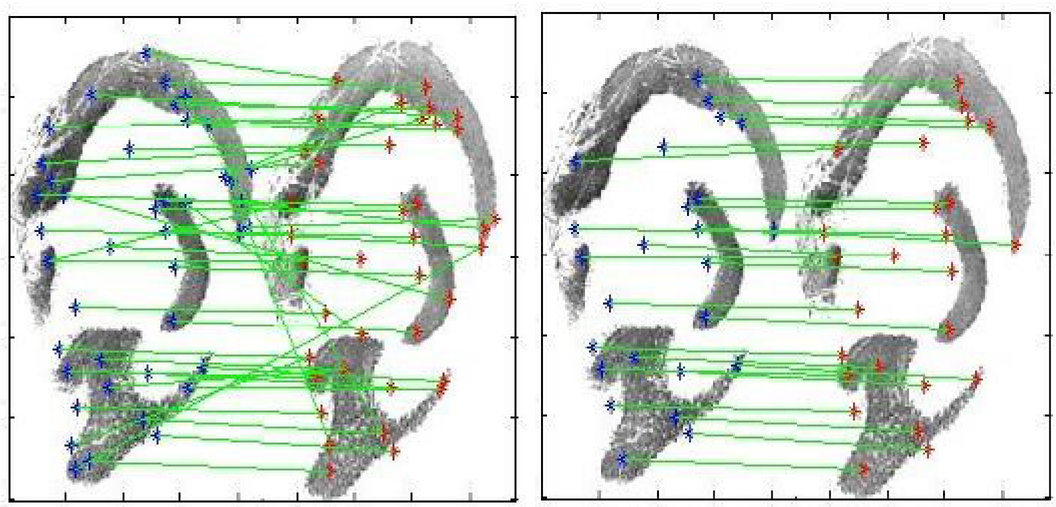


FIGURE 4.6: Matched keypoints including outliers (left) and matched keypoints including inliers only (right) [32].

4.4 Algorithm

Microsoft Visual Studio 2013 was used to implement the SIFT matching algorithm. The code for extracting SIFT features by OpenCV library [72].

Chapter 5

Experimental Results

We presented validation result of suggested approach using a database which was created by a researcher. SIFT algorithm was tested using the earmark image database that created by the researcher. The database includes 912 images belong to 50 individuals who are 29 women and 21 men. For each ear, four images were captured in three sessions by four different smartphones. 800 samples were collected in the first two sessions and 112 samples in the third one. The photos are in BMP format and a resolution of 300*260. The earmark images in were taken under same earmarks taking procedure.

Achievement assessment is acquired with TSR. The TSR value is calculated according to the following formula:

$$TSR = (1 - \frac{FAR + FRR}{Total\ number\ of\ accesses}) \times 100\%$$

where: FAR is the value that fraudsters are mistakenly accepted in the system and

FRR is the value that correct individuals are mistakenly rejected in the system.

$$FAR = \frac{Number\ of\ accepted\ imposter\ claims}{Total\ number\ of\ imposter\ accesses} \times 100\%$$

$$FRR = \frac{Number\ of\ rejected\ genuine\ claims}{Total\ number\ of\ genuine\ accesses} \times 100\%$$

Table 5.1 indicates the acquired results relating to FAR, FRR, and TSR with earmark based on verification system. The total success rate is 99.72%, while in order of FAR and FRR are decreased to 0.06% and 0.08%.

TABLE 5.1: Ear mark to ear mark achievement assessment of the suggested approach.

Set Type	Number of Person	FAR (%)	FRR (%)	TSR (%)
Woman Set	29	0,0689	0,0344	99,65
Man Set	21	0,0476	0,1428	99,10
Total	50	0,06	0,08	99,72

Table 5.2 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by woman age range. The total success rate is 99.65%, while in order of FAR and FRR are decreased to 0.0689% and 0.0344%. The highest woman age range success rate is 76-95 and the lowest woman age ranges success rate is 18-35. The success rate in the women is less than the overall success rate of the earmark verification system.

TABLE 5.2: Ear print to ear print by woman age range achievement assessment of the suggested approach.

Woman Age Range	Number of Person	FAR (%)	FRR (%)	TSR (%)
18-35	8	0,125	0	98,44
36-55	10	0,1	0	99
56-75	9	0	0,1111	98,77
76-95	2	0	0	100
Total	29	0,0689	0,0344	99,65

Table 5.3 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by man age range. The total success rate is 99.1%, while in order of FAR and FRR are decreased to 0.0476% and 0.1428%. Success rate of the highest man age range is 76-95 and 36-55. Success rate of the lowest woman age range is 56-75. The success rate in the men is lower than both the success rate of women and the overall success rate of the earmark based verification system.

TABLE 5.3: Ear print to ear print by man age range achievement assessment of the suggested approach.

Man Age Range	Number of Person	FAR (%)	FRR (%)	TSR (%)
18-35	10	0	0,2	98
36-55	6	0	0	100
56-75	5	0,2	0,2	92
76-95	0	0	0	100
Total	21	0,0476	0,1428	99,1

Table 5.4 indicates the acquired numerical results relating to FAR, FRR, and TSR with earmark based verification system by woman age range for session one (Rank-1) and session two (Rank-2). The total success rate of Rank-1 is 99.65%, while in order of FAR and FRR are decreased to 0.0689% and 0.0344%. According to Rank-1, the highest woman age ranges success rate is 76-95 and the lowest woman age range success rate is 18-35. According to Rank-2, the highest woman age ranges success rate is 56-75 and 76-95 and the lowest woman age range success rate is 36-55.

TABLE 5.4: Ear print to ear print by woman age range achievement assessment of the suggested approach for session one (Rank-1) and session two (Rank-2).

Woman Age Range	Number of Person	Rank-1			Rank-2		
		FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)
18-35	8	0,125	0	98,44	0	0,125	98,44
36-55	10	0,1	0	99	0,2	0	98
56-75	9	0	0,1111	98,77	0	0	100
76-95	2	0	0	100	0	0	100
Total	29	0,0689	0,0344	99,65	0,0689	0,0344	99,65

We can clearly see the total of FAR, FRR, and TSR values in Rank-2 are same as the values in Rank-1. The success rate in the women is less than the overall success rate of the earmark verification system. There were three months between Rank-1 and Rank-2. Each total value of FAR, FRR, and TSR in both Rank-1 and Rank-2 have been same results. Because earmarks did not change in the three-month period. Nevertheless, TSR values of 36-55 and 56-75 woman age range in both Rank-1 and Rank-2 changed. So, it shows that there are time-dependent changes in some woman earmarks.

Table 5.5 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by man age range for session one (Rank-1) and session two (Rank-2). The total success rate of Rank-1 is 99.1%, while in order of FAR and FRR are decreased to 0.0476% and 0.1428%. According to Rank-1 the highest man age range success rate is 36-55 and 76-95 and the lowest woman age range success rate is 56-75. According to Table 5.5, Rank-1 and Rank-2; FAR, FRR, and TSR values are the same.

TABLE 5.5: Ear print to ear print by man age range achievement assessment of the suggested approach for session one (Rank-1) and session two (Rank-2).

Man Age Range	Number of Person	Rank-1			Rank-2		
		FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)
18-35	10	0	0,2	98	0	0,2	98
36-55	6	0	0	100	0	0	100
56-75	5	0,2	0,2	92	0,2	0,2	92
76-95	0	0	0	100	0	0	100
Total	21	0,0476	0,1428	99,1	0,0476	0,1428	99,1

We can clearly see the total of FAR, FRR, and TSR values in Rank-2 are same as the values in Rank-1. The success rate in the women is less than the overall success rate of the earmark verification system. There are three months between Rank-1 and Rank-2. Each total value of FAR, FRR, and TSR in both Rank-1 and Rank-2 have been same results. Because man earmarks did not change in the three month period.

Table 5.6 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by woman age range for session one (Rank-1), session two (Rank-2) and session three (Rank-3). The ears of nine women were taken in three sessions. The total success rate of Rank-1 and Rank-2 are 96.30%, while in order of FAR and FRR are decreased to 0.2222% and 0.1111%. The highest woman age ranges success rate is 56-75 and 76-95. The lowest woman age ranges success rate is 36-55. The success rate in the women is less than the overall success rate of the earmark verification system.

TABLE 5.6: Ear mark to ear mark by woman age range achievement assessment of the suggested approach for session one (Rank-1), session two (Rank-2) and session three (Rank-3).

Woman Age Range	Number of Person	Rank-1			Rank-2			Rank-3		
		FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)
18-35	5	0,2	0,2	92	0,2	0,2	92	0	0,2	96
36-55	3	0,33	0	89	0,33	0	89	0,33	0	89
56-75	1	0	0	100	0	0	100	0	0	100
76-95	0	0	0	100	0	0	100	0	0	100
Total	9	0,222	0,111	96,30	0,222	0,111	96,3	0,111	0,111	97,54

According to Table 5.6, the total success rate of Rank-3 is 97.54%, while in order of FAR and FRR are decreased to 0.1111% and 0.1111%y. The total of FAR, FRR, and TSR values in Rank-2 are same as the values in Rank-1. The lowest woman age ranges success rate is 36-55. Also, the total of TSR values in Rank-3 is greater than the total of TSR values in both Rank-1 and Rank-2. The success rate of the women in Rank-3 is lower than the overall success rate of the earmark verification system. There are three months between Rank-2 and Rank-3. Woman earmarks did not change in the three month period. However, woman earmarks were changed in six months.

Table 5.7 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by man age range for session one (Rank-1), session two (Rank-2) and session three (Rank-3). The ears of five men were taken in three sessions. The total success rate of Rank-1 and Rank-2 are 96%, while in order of FAR and FRR are decreased to 0.2% and 0%. The highest man age range success rate is 56-75 and 76-95. The lowest man age range success rate is 36-55. The success rate in the men is less than the overall success rate of the earmark verification system.

According to Table 5.7, the total success rate of Rank-3 is 92%, while in order of FAR and FRR are decreased to 0.2% and 0.2%. The total of FAR, FRR, and TSR values in Rank-2 are same as the values in Rank-1.The lowest man age range success rate is 36-55 for session one (Rank-1), session two (Rank-2) and session three (Rank-3). Also the total success rate of TSR in Rank-3 is lower than the total success rate of TSR in Rank-1 and the total success rate of TSR in Rank-2. The success rate of the men in Rank-3 is lower than the overall success rate of the earmark verification system. There are three months between Rank-2 and Rank-3. So man earmarks did not change in the three month period. However, man earmarks were changed in six months.

TABLE 5.7: Ear mark to ear mark by man age range achievement assessment of the suggested approach for session one (Rank-1), session two (Rank-2) and session three (Rank-3).

Man Age Range	Number of Person	Rank-1			Rank-2			Rank-3		
		FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)	FAR (%)	FRR (%)	TSR (%)
18-35	1	0	0	100	0	0	100	0	0,2	96
36-55	3	0,33	0	89	0,33	0	89	0,33	0	89
56-75	1	0	0	100	0	0	100	0	0	100
76-95	0	0	0	100	0	0	100	0	0	100
Total	5	0,2	0	96	0,2	0	96	0,2	0,2	92

Table 5.8 indicates the acquired results relating to FAR, FRR, and TSR with earmark based verification system by different smartphone brands. iPhone 6 Plus total success rate is 99.89%, while in order of FAR and FRR are decreased to 0.06% and 0.05%. iPhone 6 total success rate is 99.94%, while in order of FAR and FRR are decreased to 0.06% and 0.05%. Samsung Galaxy S3 Mini total success rate is 99.92%, while in order of FAR and FRR are decreased to 0.05% and 0.03%. Samsung Galaxy Wgt-18150 total success rate is 99.87%, while in order of FAR and FRR are decreased to 0.09% and 0.04%. The highest TSR value is 99.94% which has iPhone 6. The lowest TSR value is 99.87% which has Samsung Galaxy Wgt-18150. Also, success rates of earmark verification of a smartphone depend on whether the smartphone has the screen protector or not. The obtained results showed that the iPhone 6 with screen protector has the highest success rate with 99.94% among other smartphones. iPhone 6 Plus does not have screen protector and the TSR value of iPhone 6 Plus is 99.89%. The success rate of smartphones of Samsung brand is lower than smartphones of iPhone brand.

Table 5.8: Ear mark to ear mark by different smart phone brands achievement assessment of the suggested approach.

Mobile Phone Brand	ScreenSaver	FAR (%)	FRR (%)	TSR (%)
Iphone6 Plus	No	0,06	0,05	99,89
Iphone 6	Yes	0,04	0,02	99,94
Samsung Galaxy s3 mini	Yes	0,05	0,03	99,92
Samsung Galaxy wgt-18150	No	0,09	0,04	99,87

Chapter 6

Conclusion and Future Work

A earmark recognition system depending on SIFT has been obtained. The feature of earmark data is computed along with a matchless template. This template includes the property of earmarks. According to experimental data, the success rate of the system is 99.72%. Results of earmark study can be used as a resource for future works.

The earmark recognition system has some important points such as: to produce property vectors from person earmark photos and to apply earmark mapping of distance. I recommend a work is to adapt the increasing usage of biometric systems which can reduce the earmark preprocessing and describe earmark local properties effectively and have better earmark recognition performance using SIFT algorithm.

The experiment watching shows that review SIFT feature description method properly can be applied to earmark recognition. Moreover, it simplifies the ear preprocessing and also does the satisfactory identification and searching through directly extracting and matching feature from earmark images. Even though the developed system has given good results with the datasets represented. SIFT is a powerful algorithm for recognition and detection for the small database but not powerful for big database.

Using the SIFT algorithm, the earmark features were effectively extracted. As future work, it is necessary to think of the large number of SIFT features on ear marks. So if you will reduce the dimension of the SIFT descriptors, which is not impairing the discrimination power and to speed up the comparison of features. Woman sets earmark success rate better than a man for the whole of the system.

According to woman age range, 76-95 age ranges success rate better than others. Because older person ear grows up so more easily recognized by the system. Woman earmarks did not change in the three month period (between Rank-1 and Rank-2) but they were changed in six months (between Rank-1 and Rank-3). As the time goes on the change in the ear is increasing.

Man sets earmark success rate worse than man for the whole of system. According to man age range, 36-55 and 76-95 age ranges success rates better than others. Man earmarks did not change in the three month period(between Rank-1 and Rank-2) but they were changed in six months(between Rank-1 and Rank-3) in the same as woman. As a person gets older the change in the ear is increasing.

The experiments done showed that earmark verification success rate varies with different smartphone brands. Because the materials used on smartphones'screens different from each other. The reason why different earmark verification success rates on the same smartphone brand are that the screen protector was used on one of the smartphone and not on the other. The obtained results show that the iPhone 6 with screen protector brand smartphone has the highest success rate which is 99.94%.

In future, increasing the number of people can enhance this study. Earmarks of the people from different geographies can be used. People from different geographies can be used to investigate the effect of genetic factors on ears. The changes can be observed more clearly when the ear recording periods are longer.

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