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HYBRID EAR RECOGNITION FRAMEWORK BASED ON PASSIVE HUMAN IDENTIFICATION



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AHMED ALI ALEMARAN

THESIS PRESENTED TO QUALIFY FOR A DOCTOR OF PHILOSOPHY

FACULTY OF ARTS, COMPUTING AND CREATIVE INDUSTRY
SULTAN IDRIS EDUCATION UNIVERSITY
2022



✓

INSTITUTE OF GRADUATE STUDIES

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ABSTRACT

Current identification of passive detection has been attention in the modern world due to the system's robustness as an ear recognition framework based on a multiclassifier and attempt to create user patterns via extracted features from ear images, which have unique individual identities. The collected features from the ear intersection points and the angles bounded between curves using different descriptors and classifiers are considered unique information used to generate unique features. The proposed framework commenced with the extraction of eight sets of features (LBP, BSIF, LPQ, RILPQ, POEM, HOG, DSIFT, and Gabor) from 2D ear images. Subsequently, ELM and SVM classifiers were trained on each set of features. Seven combination rules (MR, AR, GVAR, ICWAR, Borda, DS, and AV (GVAR, Borda, DS)) were utilized to acquire a total of 16 classifiers. Also, two optimization rules; genetic algorithm and brute force were proposed for accuracy enhancement. The AWE and the USTB datasets were utilized in the development, evaluation, and validation of an ear recognition framework dataset. So, some vulnerabilities are observed in datasets and all challenges for ear biometrics. The research findings showed that combining classifiers using different sets of features yields better performance compared to using individual classifiers. However, using one classifier or limited number is not enough to solve the problem of ear recognition with different challenges such as Pose, Occlusion, Illumination, Blurry image, Rotation, Lighting, Scale, and Translation. The validation of such a framework using the AWE dataset showed that the SVM and ELM in combination with modern descriptors managed to enhance the recognition. Rank-1 accuracy also reached 99% with Genetic Algorithm optimization, and 98% with brute-force AR and brute-force GVAR. These results are compared to other results in the literature and found to be superior. In conclusion, the main findings showed that the proposed framework consisting of two classifiers SVM and ELM trained with selected features and the combination rules managed to attain higher accuracy in-ear recognition compared with previous studies. This ear recognition framework is a major step towards the recognition of individuals from ears in real-world conditions. This study implies that the proposed ear recognition framework based on ELM and SVM classifiers with combination and optimization rules can be utilized to improve the effectiveness of passive human recognition where security is of utmost importance.





RANGKA KERJA HIBRID BAGI PENGENALAN TELINGA BERDASARKAN PENGECEMAN MANUSIA SECARA PASIF

ABSTRAK

Kajian ini bertujuan untuk membina kerangka pengecaman telinga berdasarkan pengelasan mesin pembelajaran ekstrem (ELM) dan mesin vektor sokongan (SVM). Rangka kerja yang dicadangkan bermula dengan pengekstrakan lapan set ciri (LBP, BSIF, LPQ, RILPQ, POEM, HOG, DSIFT dan Gabor) dari gambar telinga. Selepas itu, pengelasan ELM dan SVM dilatih dengan setiap set ciri. Tujuh peraturan gabungan (MR, AR, GVAR, ICWAR, Borda, DS dan $AV_{(GVAR, Borda, DS)}$) digunakan untuk memperoleh 16 pengklasifikasi. Juga, dua peraturan pengoptimuman; algoritma genetik dan daya keras dicadangkan untuk peningkatan ketepatan. Kumpulan data AWE dan USTB digunakan dalam pembinaan, penilaian, dan pengesahan set data kerangka pengecaman telinga ini. Hasil kajian menunjukkan bahawa penggabungan pengklasifikasi dengan menggunakan set ciri yang berbeza dapat menghasilkan prestasi yang lebih baik berbanding dengan menggunakan pengelasan individu. Pengesahan kerangka tersebut yang menggunakan set data AWE menunjukkan bahawa SVM dan ELM yang digabungkan dengan deskriptor moden berjaya meningkatkan pengecaman. Ketepatan peringkat-1 juga mencapai 99% dengan pengoptimuman Algoritma Genetik, dan 98% dengan daya keras AR dan daya keras GVAR. Hasil ini didapati lebih baik apabila dibandingkan dengan hasil kajian-kajian lain dalam literatur. Sebagai kesimpulan, penemuan utama menunjukkan bahawa kerangka kerja yang dicadangkan terdiri daripada dua pengklasifikasi SVM dan ELM yang dilatih dengan ciri-ciri terpilih dan peraturan kombinasi telah berjaya mencapai ketepatan yang lebih tinggi dalam pengecaman telinga. Kerangka pengecaman telinga ini merupakan langkah utama untuk mengenal pasti individu melalui telinga dalam dunia nyata. Kajian ini memberi implikasi bahawa kerangka pengecaman telinga yang dicadangkan berdasarkan pengklasifikasi ELM dan SVM dengan peraturan kombinasi dan pengoptimuman dapat digunakan untuk meningkatkan keberkesanan identifikasi pasif manusia bagi keselamatan kerana ia adalah perkara yang sangat penting.





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CHAPTER 1

GENERAL INTRODUCTION



An interesting individual anatomical part that has gained much popularity recently as passive, physiological biometrics systems is the passive human recognition framework based on ear recognition via image captured through digital cameras. The term biometrics can be defined as employing certain behavioral or physiological characteristics, based on which a person can be identified or authenticated. Usually, a measurable characteristic of human beings is taken so that automatic recognition can be facilitated. Physiological characteristics depend on certain structural information regarding body-like shape (body, ear, hand, and face), color (hair, skin), weight, fingerprint, odor, height, texture, iris, and retina. Behavioral characteristics are dependent on the behavior of an individual such as pattern (respiration, eye blinking, keyboard typing), body posture, handwriting, gait, speech, and heartbeat (Anwar et al.,





2015). Many singular features can be associated with the human ear, which allows identifying specific individuals (Choraś, 2008; Wahab et al., 2012).

The primitive technologies of the past still seem to have cast an impact on the quick development of biometrics methods aimed at individual recognition. However, with advances in technology along with the availability of various options for sensing and powerful hardware to perform calculation, the adoption of biometrics-based recognition systems turned out to be more feasible as well as reliable.

In biometrics-based recognition, the extraordinary, unique qualities of an individual are utilized, which are accessible in the ear, face, fingerprint, iris, signature, etc. Employing biometrics increases complexity in the recognition system, which would bring difficulties. Some of the reasons why biometrics systems for recognition are preferred as a strategy when compared to PIN-based techniques and traditional passwords are:

1. Physical presence: The individual that must be identified has to be physically present where the biometrics framework has been installed. Thus, biometric recognition can be said to be more secure and authentic.
2. The data such as a password or a PIN need not be memorized or recalled. These data involved in biometric verification are constantly fed by the individual themselves.





3. Fewer chances for forgery and fabrication: There is a minimal chance that the biometric identity of someone would be faked or forged (Choraś, 2005; Wahab et al., 2012).

In the upcoming section, the researcher will present the generic architecture of a biometric system.

1.2 Human Biometric Authentication

A biometric framework can be utilized in two models: the recognition model and the verification model. The first model includes matching the images versus the templates corresponding to all the individuals in the database. This takes considerable time depending on the size of the database, which means comparing one to many. The second model includes matching with only those templates corresponding to the claimed identity. This does not take more time because it makes a one-to-one comparison.

Anwar et al., (2015) analyzed the biometric framework requirements and proposed the following characteristics that biometric features should possess for it to be rendered as appropriate for successful authentication:





1.2.1 Universality

It should be a characteristic that is common to all individuals; it should seldom be lost through accident or disease.

1.2.2 Uniqueness

The same value of the biometric characteristics should not be found in two individuals.

1.2.3 Permanence



It should not be subject to considerable change based on age or disease; this means the features should be invariant with time.

1.2.4 Collectability

It should be collectable from any individual in any case.

1.2.5 Acceptability

The framework should be acceptable to the people concerned as a part of their daily routines; otherwise, the framework will not be used.



1.2.6 Measurability

The possibility of acquiring and digitizing the biometric features by utilizing some appropriate sensors or devices without causing any disturbance.

1.2.7 Circumvention

It should be able to deal with individual cases effectively.

Unfortunately, it is very difficult to have a biometrics framework that fully satisfies all the above issues. Depending on the application needs, one should choose

 05-4506832  the most appropriate biometrics.  Perpustakaan Tuanku Bainun
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Table 1.1 shows the difference between the biometric properties (1 means maximum, 0 means medium and -1 means minimum). Biometrics refers to the utilization of certain physiological or behavioral characteristics to authenticate or identify the person. It is a measurable characteristic of a human that can be utilized for automatic recognition. By comparing these properties, it demonstrated that the features of an ear are expected to be very distinctive in establishing the identity of human (Anwar et al., 2015).

Table 1.1

Comparison of some of the biometric properties, where 1 means maximum, 0 means medium and -1 means minimum (Jain et al., 2004)

Identifier	Biometrics	Universality	Uniqueness	Permanence	Collectability	Acceptability	Measurability	Circumvention
Face		1	1	0	1	1	1	-1
Fingerprint		0	1	0	0	0	1	1
Ear		0	1	1	1	1	1	-1
Iris		0	1	0	-1	-1	1	-1
Palm print		0	0	0	0	0	1	0
Signature		-1	1	0	0	0	1	1
Voice		1	0	0	1	1	1	1
Gait		1	0	0	1	1	0	-1
Keystrokes		0	0	0	0	1	0	0

In the next section, the researcher provides the ear biometrics, its steps, and the motivation of the study.

1.3 Ear Biometric:

The study of otomorphology or, as it is more commonly known, aerology, is the study of the physiognomy of the external ear for utilization in biometrics. The first known researcher to suggest the study of ears was Bertillion in the 1890s, but it was not until



M. Burge & Burger (1998) were among the early researchers who attempted the development of automatic ear biometric method. They found ear biometrics to be promising because it is robust and simple to be extracted, like a fingerprint. It is also suitable for passive identification, which is like face recognition. Human ears have been utilized as the main feature in forensic science. Lately, ear-prints found at a crime scene, have been utilized as proof in several cases in the Netherlands and the United States (Lakshmanan, 2013). According to Lammi (2004), the most suitable biometrics for human recognition or authentication would be the iris. He based it on the parameters shown in Table 1.2 that were considered for comparison of the methods. The comparison includes the comfort during of the verification, accuracy which is related to error rate, availability, or the readiness of the recognition method when and where it is needed and lastly the cost that should be taken into consideration. The DNA would also be a good choice, but the duration of the recognition and authentication process is too long for everyday use. The ear recognition is in the average class in all the four parameters in Table 1.2.



Table 1.2

Biometric suitability for recognition and authentication purposes.

Biometric Trait	Comfort	Accuracy	Availability	Costs
Fingerprint	0000000	0000000	0000	000
Signature	000	0000	00000	0000
Facial geometry	000000000	0000	0000000	00000
Iris	00000000	000000000	00000000	00000000
Retina	000000	00000000	00000	0000000
Hand geometry	000000	00000	000000	00000
Finger geometry	0000000	000	0000000	0000
Ear form	0000	0000	0000000	00000
Voice	0000	00	000	00
DNA	<i>0</i>	0000000	000000000	<i>000000000</i>
Odor	<i>?</i>	00	0000000	<i>?</i>
Keyboard strokes	0000	<i>0</i>	<i>00</i>	0

(Bold font is used to show the best performing method for each parameter, and the worst performance is represented by italicized font) (Adapted from Lammi, 2004).

1.3.1 Anatomy of the Human Ear

Biometrics considering the individual ear is practical because the ear anatomy is unique for each individual and the elements for estimating the anatomy are comparable over time. The ear does not have a totally arbitrary structure, it is comprised of standard elements simply same the face. The parts of the human ear are minimal compared with the eyes, mouth, nose, and other facial elements. The natural human ear contains an

external rim (helix) and ridges (anti-helix), concha, and tragus (small prominence of cartilage). Figure 1.22 displays the locations of the anatomical features:



Figure 1.2. Anatomy of the Human Ear (Omara et al., 2016)

1. *Helix*
2. *Crus Antihelices,*
3. *Antihelix,*
4. *Scapha,*
5. *Antitragus,*
6. *Cavum Conchae,*
7. *Fossa Triangularis,*
8. *Crus Helices,*
9. *Tragus, and*
10. *Lobule (Ear Lobe)*



Human ears start to appear and grow between the fifth and seventh weeks of pregnancy. At this stage, the embryo's face adopts more definition as nostrils, mouth and ear become apparent (Arbab-Zavar & Nixon, 2011a). Ear growth after the seventeen weeks of birth is highly linear. The average of stretching is nearly five times greater than normal during the period from seventeen weeks to the age of eight years, after which it becomes constant until around the age of seventy years when it again increases (Abaza et al., 2013; Arbab-Zavar & Nixon, 2011a; Dinkar & Sambyal, 2012; Lu Lu et al., 2006; J. Zhou et al., 2012).

1.3.2 Passive Ear Biometrics System



In the passive biometrics system, gaining important human anatomical parts of the ear depends on the ear images acquired from cameras that would show the faces and ears. Both of those body parts are important, as they allow for identifying many individuals and can be applied to efficient biometrics systems for many applications (Wahab et al., 2012). Nevertheless, there are many advantages to utilizing the human ear as a source for individual recognition as it is smaller in size, stable in features and usually of monochromatic color. Furthermore, to enable effective hearing, the ear is often not hidden underneath anything. In comparing between the ear and face recognition systems, ear images usually are not occluded by glasses, cap, or makeup. Nevertheless, occlusion by the hair or earphones is not impossible, but during the real-time application, asking the individual to make the ear visible would not be a problem and would not require much time (Choraś, 2005).



There are two main categories in biometric as shown in Figure 1.33. The first category is physiological biometric based on an anatomical feature of an individual body. The second category is a behavioral feature of individual action, and it identifies individuals by their activities. Both categories can be either passive biometric that it can be successful without individuals even knowing that they have been analyzed and does not require individuals' active participation. Active biometrics require individual cooperation (Wahab et al., 2012).

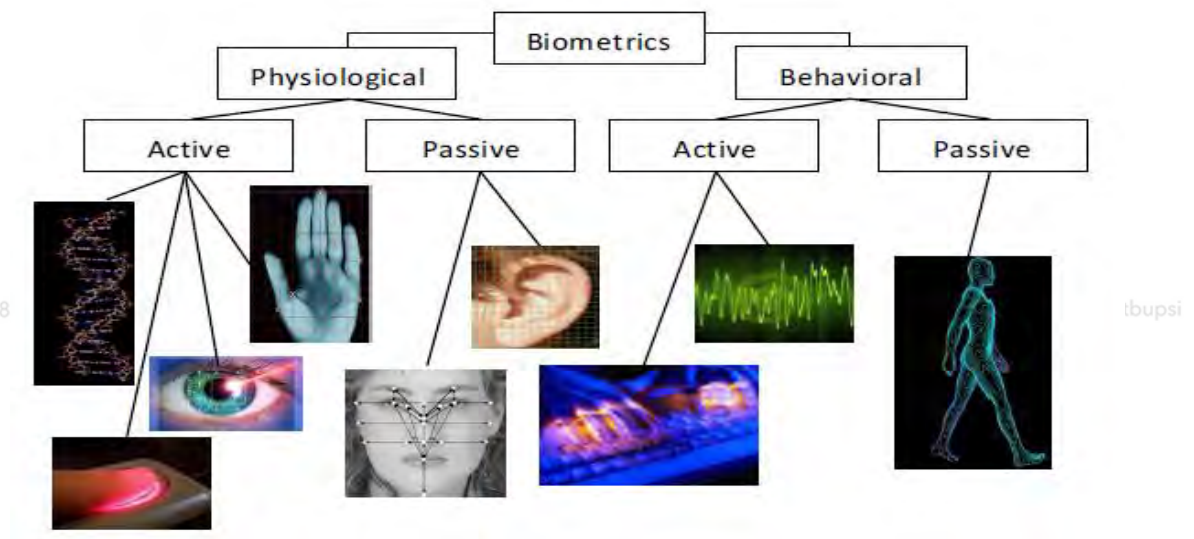


Figure 1.3. Biometrics' categories and technologies (Wahab et al., 2012)

An important classification of biometric techniques is the division into physiological and behavioral biometric technologies. Physiological technologies seek unique characteristics that human possess and do not change dramatically over time. Behavioral biometrics, furthermore, uses a method whereby individuals do something to uniquely identify or reveal themselves and that does change over time. The researcher has physiological biometrics technologies such as fingerprint (analyzing fingerprint patterns), face location (measuring facial features), DNA (analyzing genetic



makeup), iris scan (analyzing blood vessels in the eye), and ear (measuring ear characteristics). Behavioral biometrics technologies include a signature (analyzing signature dynamics), voice recognition (analyzing vocal behavior), and keystroke patterning (measuring the time spacing of typed word) (Choraś, 2005; Omara et al., 2016; Prakash & Gupta, 2015; Shoaib et al., 2016).

Notwithstanding the importance of passive security (tracking) and verifying identity (without the person's knowledge to avoid putting him/her in a critical situation), the laws in many European countries and the United States of America, forbid the use of passive security. This prohibition includes different kinds of passive security, such as tracking and verifying recognition through telephone conversation of people without their knowledge (Choraś, 2008; Wahab et al., 2012). Photographing a person without him/her knowledge is considered illegal and this may be the reason for much litigation. The laws in some countries force the supermarkets that use monitoring cameras to declare the existence of these cameras.

1.4 Ear Biometrics and Its Motivations

Generally, the ear recognition framework would involve three steps. The first step is the detection of the position of the ear from the side of the profile face, which is not an easy task because of the location, scaling, and orientation of the ear image. The second step includes the extraction of the related features from the localized ear image acquired in the previous function. And the last step performs a ranking of images built on the





extracted feature vector in the second step. The following are among the reasons to use ear biometrics recognition:

1. The individual's ears have been utilized and accepted as the main feature in forensic science (Anwar et al., 2015; Badrinath & Gupta, 2009).
2. Throughout a human's life, the ear pattern is highly stable. The shape of the human ear is stable between the age of 8 years to 70 years, which means that the ear shape is very much stable for the rest of the life (Abaza et al., 2013; Anwar et al., 2015; Lakshmanan, 2013).
3. The changing expressions do not affect the ear, as on the face. The ear has many advantages as uniform color; uniqueness of outer ear shape that does not change because of emotion including happiness, fear, or surprise etc., as in Figure 1.41.4. (Arbab-Zavar & Nixon, 2011a).
4. Convenient distance for passive identification. Ear human images can be captured from a flexible distance even without the knowledge of individuals, by utilizing only a digital camera (Choraś, 2008; Wahab et al., 2012).
5. The ear size is more efficient for recognition framework and recognition task. It is larger than a fingerprint, retina, etc., and smaller than the face, and hence ear image can be captured easily (Chora's, 2005; Ghoualmi et al., 2016; Nanni & Lumini, 2007).



6. The appearance of the ear is firmly fixed in the middle of the side profile face as in Figure 1.41.4 so that the intermediate background is predictable. The ear is not affected by cosmetics and eyeglasses (S. M.S. Islam et al., 2009; Lakshmanan, 2013).
7. It is not hidden underneath any things such as clothes or cap (Choraś, 2005).



Figure 1.4. Ear image (Vélez et al., 2013)

1.5 Ear Biometrics Limitations

There are certain limitations in-ear biometrics generally, as described below:

1. The occlusions of the ear by the hair as in Figure 1.5 (a), or earring as in Figure 1.5 (c), or sunglasses or earphones and scarves that are usually worn by Muslims in Islamic countries. The main problem with ear human recognition is the failure to get a full ear image or the loss of a part of the ear image since it is the main

requirement for ear biometrics as shown in Figure1.5 (d and e) (Anwar et al., 2015).

2. Change in the pose as in Figure1.5 (g), and the illumination of ear images as in Figure1.5(a). The presence of glasses may also reduce the system's performance. (Badrinath & Gupta, 2009)

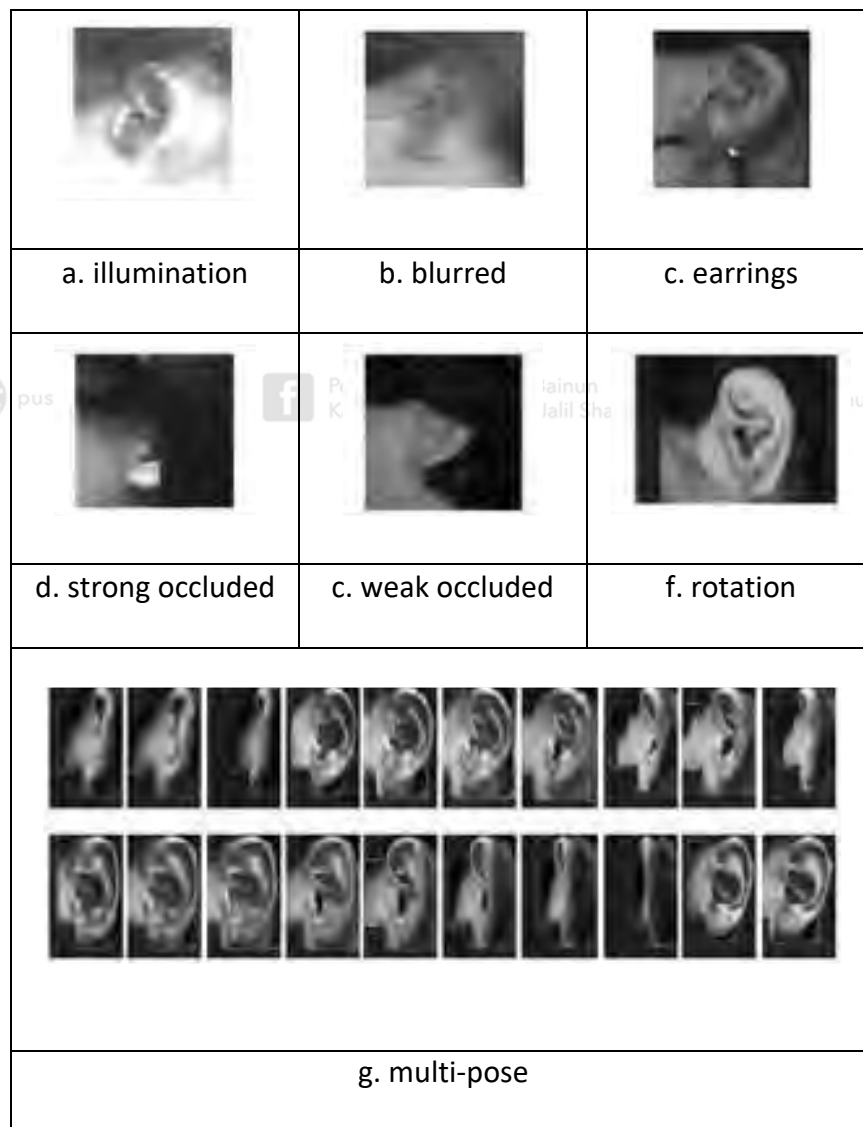


Figure1.5. Problems in-ear biometric systems (Kurniawan et al., 2012)

3. One of the greatest challenges on-ear segmentation is the blurry image as in Figure 1.5(b), so it needs a suitable distance in the outdoor environment for the best recognition (Anwar et al., 2015).
4. Every biometric detection model such as an ear biometric has an error rate due to its inherent features even when operating in a constrained environment (Jain et al., 2004).
5. Spoofing: This can be defined as intentionally cheating the framework to make it accept an artificially prepared biometric as a true biometric. And some factors that can affect the ear are background, lighting, camera sensor, etc. (Bustard & Nixon, 2010; Wahab et al., 2012).
6. Stolen template biometric would be disastrous. A stolen template remains for life since it is not a digital certificate or a password that can be exchanged (Anwar et al., 2015; Choraś, 2005).

1.6 Problem Statement

Human recognition using biometric features has been researched extensively in recent years. For instance, using iris biometric features requires high-resolution cameras and costs are usually very high. Therefore, this kind of system is only for some specific agencies rather than for public use. Similarly, face images have many factors, glasses, and human emotions, which might affect the recognition accuracy. On the other hand,



less attention was paid to using ears as a biometric feature for human recognition (Alaraj et al., 2010). Challenges in Figure 1.5 needs the development and design of a robust ear biometric recognition method that has a high level of accuracy and performance within the cumulative match characteristic (CMC) curve and the receiver operating characteristic (ROC) curve. There are eight types of features, namely BSIF, LBP, RILPQ, LPQ, HOG, DSIFT, POEM, and Gabor. All use the dual main classifiers SVM and ELM. Both are trained using all feature types, which consequently provide 16 trained classifiers. Subsequently, all pass to aggregation or combinatory layers that work to select the best classifier according to the aggregation rules. Seven rules, namely AR, MR, ICWAR, Borda, GVAR, DS, and AV_(GVAR, Borda, DS) were compared in this study. At this point the accuracy between 49.60% (Hassaballah et al., 2019) and 75.6% (Hansley et al., 2018). However, a critical problem concerning this technology is the accuracy of extracted features from ear biometric in the case of human passive recognition in different security sectors. This problem is a big challenge in this type of technology, where the weak features that extracted from ear biometric leads to serious risks in term of passive identification. In other terms, a biometric recognition system requires the discovery of unique features that can be measured and compared to correctly identify subjects (Galdámez et al., 2016). This problem will also have an impact on the reliability of the recognition framework and the rights of stakeholders.

However, using one classifier or limited number is not enough to solve the problem of ear recognition with different challenges such as Pose (Yazdanpanah & Faez, 2010), Occlusion (Guermoui et al., 2016), Illumination (Wu et al., 2009), Blurry image, Rotation, Lighting, Scale and Translation (Emeršič et al., 2017). Moreover, adequate results are not obtained with the simple implementation of combination rules,





unless an optimization approach is designed having the best features and classifiers for ear recognition. In other terms, a biometric recognition system requires the discovery of unique features that can be measured and compared to correctly identify subjects. There are some known techniques for ear recognition especially in 2D and 3D images, as the strategies based on appearance, force transformation, geometrical features, and the use of neural networks (Galdámez et al., 2016).

There has been less research on combining classifiers to train a high number of feature types. Moreover, adequate results are not obtained with the simple implementation of combination rules, unless an optimization approach is designed having the best features and classifiers for ear recognition. Ear recognition that employs classifiers combination, ensemble classification and multiple classifiers has been put forward. These features have been extracted based on the logic of combining them in an aggregative categorization way. The literature comprises a broad range of classifiers, extreme learning machine (ELM) (Cao & Lin, 2015) and support vector machine (SVM) (Wu et al., 2009), which are considered advanced classification approaches, while it is still debatable as to which of these gives the best classification performance. However, as various types of features for ears as well as different classifiers are available, a combination framework or approach would be beneficial to obtain the best of them.

Compared to appearance-based features, our features are more effective for matching ear depend on the result accuracy. Moreover, our features are complementary to the appearance-based features, and better differentiation performance can be obtained by combining these two types of features and combining different types of





features may be more effective in improving recognition performance. By combining two features, better performance can be achieved from individual methods (Omara et al., 2016). Yazdanpanah & Faez (2010) efficiently combined different features and modalities which provides an effective set of different types of features and modalities. Feng & Mu (2009) suggested the problem of multi-class classification (where the class number is greater than 2) to be solved by a set of classifiers. The consolidation strategy needs to create SVM and ELM classifiers; each one is trained on data from some classes. The study by Arbab-Zavar & Nixon (2011b) had seen the improvement of the hybrid classification which is maintained even at large ears occlusion. The hybrid classification maintains good performance because of the analysis of the outer ear when collecting more than one feature. In (Galdámez et al., 2016), their proposed system combined a series of algorithms that yield individually significant results, and when combined, produced a higher degree of durability with significant improvement in issues such as changes in image brightness and perspective. Mostly, this evidence aims to establish the presence or absence of a particular individual under investigation (Chowdhury, Bakshi, Sa, et al., 2018b).

For many years, people have debated about ear recognition but still used old techniques and less accuracy, and some of them try to solve the ear recognition by using one classifier. Not many studies used more than one classifier to solve the problem of ear recognition with different challenges. The authors in the literature review extracted a set of features from the human ear. Notwithstanding the importance of passive security (tracking) and verifying identity (without the person's knowledge to avoid putting him/her in a critical situation), the laws in many European countries and the United States of America, forbid the use of passive security. This prohibition includes





different kinds of passive security, such as tracking and verifying recognition through telephone conversation of people without their knowledge (Choraś, 2008; Wahab et al., 2012). For recognition as well as processing, the two-dimensional (2D) digital images are stressed upon since standard digital cameras are more common and cheaper versus three-dimensional (3D) scanners, which make the study more appropriate with regards to real-life control access applications. Analysis techniques with 3D ear human image cannot be considered for forensic science or police procedures. It was also shown that 2D human ear images tended to be more robust against occlusion. On the other hand, 3D human ear images were shown to be more robust against pose and illumination (Chen et al. 2017; Yuan and Mu 2012). Photographing a person without his/her knowledge is considered illegal and this may be the reason for litigation. For example, the laws in some countries force the supermarkets that use monitoring cameras to declare the existence of these cameras.



Researchers have been attempting to create user patterns via extracted features from ear images, which have unique individual identities. The collected features from the ear intersection points and the angles bounded between curves using different descriptor and classifiers are considered unique information used to generate unique features. Six studies attempted to use multiple classifier approach to recognize the human ear, as shown in Table 1.31.3. It shows studies with different types of techniques that were compared in terms of the challenges that were proposed to be solved in their studies.



Table 1.3

Hybrid ear recognition with challenges for each study

References	Pose	Occlusion	Illumination	Blurry	Rotation	Lighting	Scale	Translation
(Chowdhury, Bakshi, Sa, et al., 2018a)	x	x	x	x	/	x	x	/
(Galdámez et al., 2016)	x	x	/	x	x	x	x	x
(Guermoui et al., 2016)	x	/	x	x	x	x	x	x
(Yazdanpanah & Faez, 2010)	/	x	/	x	x	x	x	x
(Alaraj et al., 2010)	x	x	/	x	x	x	x	x
(Wu et al., 2009)	/	x	/	x	x	x	x	x

In (Chowdhury, Bakshi, Sa, et al., 2018b), it was very evident that the separability of any AWE dataset is embarrassingly lower than the index obtained for other formulations. This confirms that the three databases: IITD-I, AMI and WPUT, which are captured by individual cameras, can each be well separated. But the introduction of the fourth AWE database, in which multiple cameras are used to acquire images, reduces separability. The assumption is that a good rating for images from three sources will be produced and we will not get a good rating including AWE. This is an indication of the difficulty of dealing with the AWE database as it contains images of various types. While in (Galdámez et al., 2016), the integration of two algorithms in the ear recognition system is the main result of this study. The method that was used in this research is an attempt to compile some of the most common methods in the recognition process. The project is not presented as a unique and exceptional study, but it was based on the methods proposed by other researchers. The study combined and compared those



methods and defined a set of these methods to successfully implement a fully functional system that would be able to recognize any person through his ear and demonstrate the success of the combined methods (by combining features and classifiers).

In (Guermoui et al., 2016), the combination of the features produced better results than the case when either one is considered alone. The experimental results show that the combination method is more robust in-ear occlusion, especially on larger scales. In (Alaraj et al., 2010), a framework has been proposed to improve the accuracy of human recognition. The frame was tested on the ear image database to assess its reliability and accuracy of recognition. Empirical results showed that the framework achieved higher discrimination accuracy and performance as compared to other existing methods. The recognition accuracy and calculation time was verified for different image sizes and factors, and most of the engineering methods used in the recognition system did not usually achieve reliable results. This is because if any error occurred in the measurements of the geometric relationships between parts of the ear, it would lead to a classification error, which threatens the entire recognition accuracy of the system. However, all these measurements require more computational time, which should be avoided in any recognition system especially when using large image databases. The recognition system is also evaluated against some specific criteria. These criteria are considered when making some comparisons between human behavior and an automated biometric system in terms of the ability to recognize some of these criteria, as well as the evaluation of the framework against these criteria. In (Wu et al., 2009; Yazdanpanah & Faez, 2010), the recognition rates were very low for ear recognition in the single classifier but in multiple classifiers, it increased the ear recognition rate, but it could not achieve the best result in databases with lighting changes and position



differences. The excellent performance shown by the proposed method is a direct result of the approach that greatly improves average accuracy over all previous ear recognition methods.

This thesis aimed at building a framework that can interactively detect as well as identify decisions based on the human ear with maximum accuracy. Hence, this thesis presents highly efficient classification algorithms that were derived via the existing feature extraction methods employed in the most recent works combining global and local data in different poses and occlusion of ear images on the AWE database. So, some vulnerabilities are observed in datasets and all challenges for ear biometrics are shown in Figure 1.1.6 and further discussed in Section 2.4.

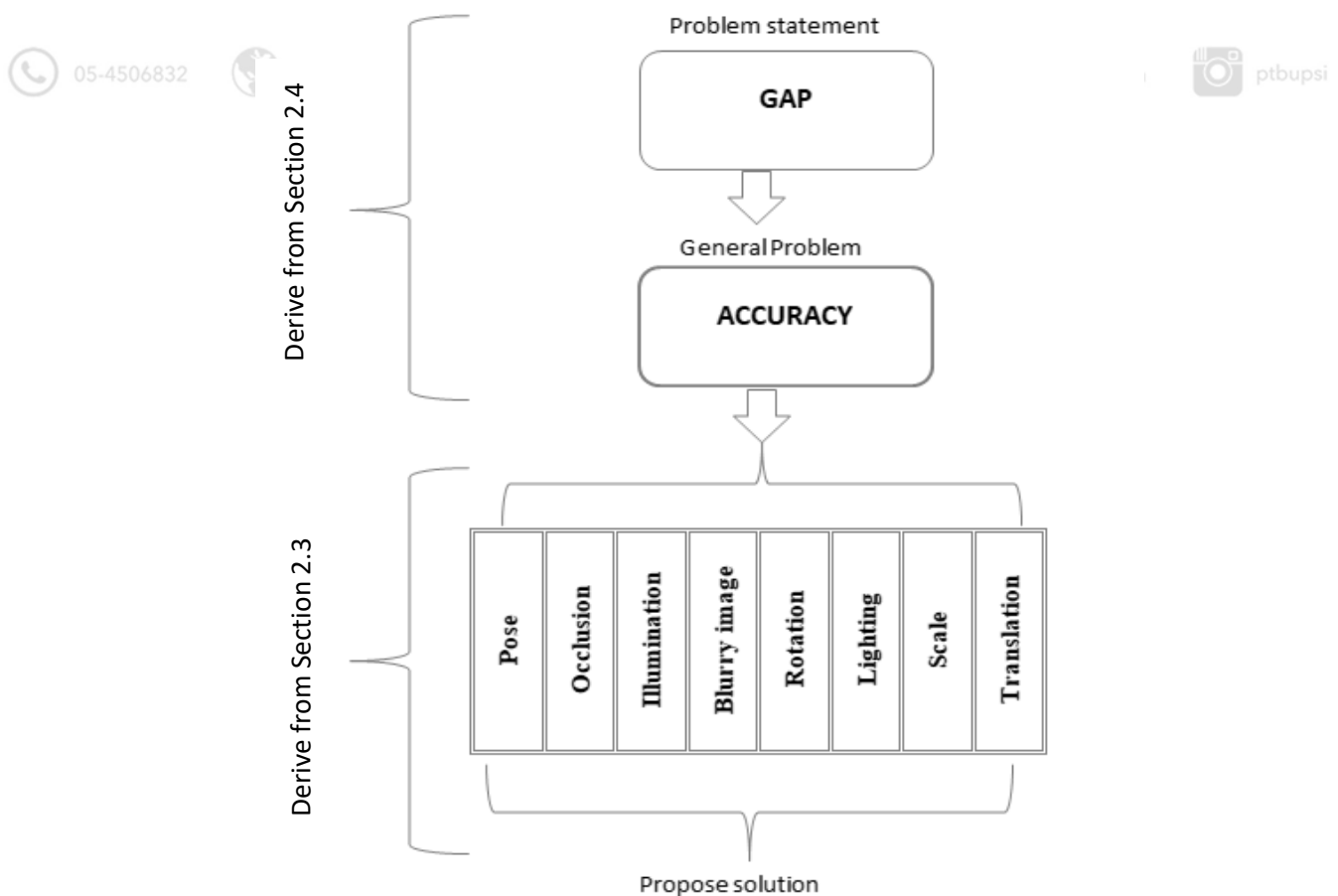


Figure 1.6. Flowchart for problem statement

1.7 Objectives

The key aim of the thesis is to build an ear-based recognition framework with the following objectives:

1. To investigate current methods developed by other researchers regarding ear recognition technologies.
2. To propose a set of features using the best descriptors to be trained with SVM and ELM classifiers along with a common set of features associated with hybrid ear recognition.
3. To design an optimum combination rule using brute force and Genetic Algorithm optimization (GA) for performance enhancement by utilizing the proposed set of trained classifiers.
4. To evaluate the result achieved by the proposed combination rules.

1.8 Research Questions

The objectives of this study aim to answer the following research questions:

1. What is the current state of ear recognition technologies?
2. What are the suitable descriptors for ear biometric features and suitable classifiers for its training?
3. How to build an optimum combination rule by utilizing the proposed set of trained classifiers to enhance the accuracy of the ear biometric recognition?
4. How is the performance of the proposed method of ear biometric recognition as compared with the previous methods?

1.9 Thesis Outlines

The outlines of the thesis will be as follow:

1.9.1 Chapter 1

This chapter covers the concepts and importance of ear biometrics, motivation, and a problem for human ear biometric. The problem statement, the aim of this proposal, research questions and research objectives are also presented.

1.9.2 Chapter 2

This chapter focuses on the literature theory about ear recognition. It includes two parts: a systematic review and the theoretical background of techniques.

1.9.3 Chapter 3

This chapter covers the concepts and importance of combinatory classification framework, classifiers representation, classifiers combination, and the optimization of combinatory classification framework.

1.9.4 Chapter 4

This chapter covers the experiments of individual features, SVM and ELM. The experiments for all techniques on the thesis are also presented in this chapter.

1.9.5 Chapter 5

This chapter covers the evaluation of individual features, SVM evaluation on individual features, ELM evaluation on individual features, Combinatory Rules evaluation on individual features, Combinatory Rules evaluation on all features, and comparison with previous works are also presented in this chapter.

1.9.6 Chapter 6

This chapter covers the general summary for the thesis. Limitations and future works are also presented in this chapter.