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A Review Paper on Ear Recognition Techniques: Models, Algorithms and Methods

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Abstract: The ear recognition techniques in image processing become a key issue in ear identification and analysis for many geometric applications. This paper first reviews the source of ear image identification, compares the different applied models being currently used for the ear image modeling, details the algorithms, methods and processing steps and finally tracks the error and limitation from the input database for the final result obtain for ear identification.The standard datasets that have been used are two different databases which are IIT Kanpu databases database and benchmark database from the University of Science and Technology Beijing (USTB) consisting at least of 500 images from each database.

Key words: Biometric system; Feature extraction; Preprocessing; Image understanding; Ear identification.

INTRODUCTION

A biometric system is a pattern recognition system that establishes the authenticity of a specific physiological or behavioral characteristic possessed by a user (Jain *et al*. 2000). It is regarded as the most secure and accurate authentication tools for verifying human identity (Kumar & Srinivasan 2012). With the presence of threats of terrorism and other criminal activity undermining the safety of nations and people, the need for biometric techniques is apparent (Kumar & Srinivasan 2012). However, due to the requirement of well-controlled environments or other reasons, most experiments on biometric systems do not live up to their expectations nowadays. As each biometric has its strengths and weakness, no single biometric is expected to effectively meet the requirements of all applications (Jain *et al*. 2004). Thus, the match between a specific biometric and an application is determined depending upon the requirements of the application as well as the properties of individual biometric characteristics (Ulandag *et al*. 2005). Examples include fingerprints, iris and retinal scans, hand geometry (Woodward 2001), signature, voice, DNA, ear and other measures (Jain and Prabhakar 2004).

The use of various human features as a tool for personal identification is older than many realize, and this includes the ear. As Hurley *et al*. (2007) have observed, ear biometrics as a significant field of research has received inadequate attention in the scientific community, especially in comparison to the more popular methods of utilizing face, eye, or fingerprint in recognition and identification purposes. Nonetheless, ears played a noteworthy role in forensic science for decades, principally in the United States, where Iannarelli (1989) developed an ear classification system based on manual measurements, which has been in use for many years.

The ear had particular advantages over the more traditional areas used in biometrics, specifically inasmuch as it has a rich and stable structure that does not change significantly as an individual ages (Hurley *et al*. 2007). Moreover, whilst the face changes radically based on expression, that problem does not exist with ears. In addition, the immediate background of the ear is very predictable (since it is always located on the side of the head), whereas facial recognition typically requires a controlled background for accurate capture a situation that is obviously not always present (Hurley *et al*. 2007). Unlike iris, retina, or fingerprint capture (which are contact biometrics), the ear does not require close proximity to achieve capture.

The qualities mentioned above make ear biometrics as promising as the field of facial recognition, since it is also a passive identification method (Purkait 2007; Yuan & Mu 2005; Yuan *et al*. 2007). As the field becomes more precise, biometric identification is recognized as a very efficient method, especially when compared to more traditional forms of identification. As a result, the field has attracted a great deal of interest and research activity (Jawale & Bhalchandra 2012). The human ear is considered one of the best features for passive identification, and may become an invaluable tool used in security for highly sensitive areas. The ear has "desirable properties such as shape, universality, uniqueness and permanence" (Chen & Bhanu 2007).

It is now widely accepted that the shape and appearance of the ear is unique to each individual and comparatively fixed during the lifetime (Iannarelli 1989; see also, Kumar & Srinivasan 2012). No one can prove the uniqueness of the ear, numerous studies provide empirical supporting evidence. According to reports, the variation over time in a human ear is most noticeable during the period from four months to eight years old and

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over 70 years old. The ear growth between four months to eight years old is approximately linear, and after that it is constant until around 70 when it increase again” (Kumar & Srinivasan 2012).

Whilst there are some small changes that take place in the ear structure, these are restricted to the ear lobe and are not linear (Kumar & Srinivasan 2012). Such stability and predictable changes make ear biometrics an exciting realm for future research. Commonly, the acquisition of ear images and facial images are very similar, meaning that the former can potentially be used in the same situations.

2. Ear Recognition Development:

The most prominent part is the ear’s outer rim called the helix, which merges into the lobe at the bottom. The antihelix is the rounded brim of the Concha, which runs almost parallel to the helix. It forks into two branches at the top, forming the superior and the inferior cruses of antihelix. The concha is a shell-shaped cavity, which merges into the incisura. The incisura has two small bumps on either side named the tragus and the antitragus. The concha is divided into two parts by the crus of helix which is the horizontal part of the helix (Anika Pflug & Christoph Busch 2012). Figure 1 shows the common terminology of the external ear.

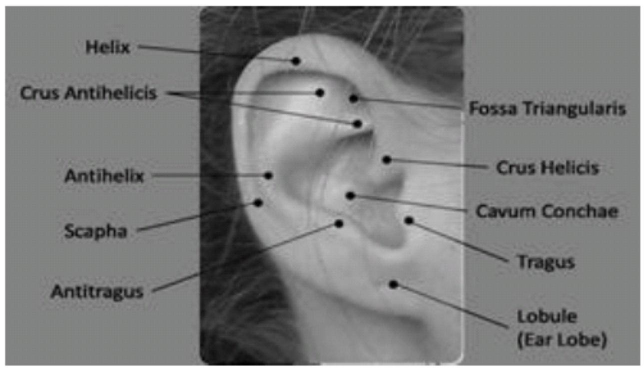

Fig. 1: The Terminology Structure of the Ear.

Nowadays some applications of Ear Recognition don’t require ear detection (Samuel *et al*., 2011). In some cases, ear images stored in the databases are already normalized. There is a standard image input format, so there is no need for a detection step. However, the conventional input images of computer vision systems are not that suitable. They can contain many items or ears. In these cases ear detection is mandatory. It’s also unavoidable if we want to develop an automated ear tracking system. For example, video surveillance systems try to include ear detection, tracking and recognizing. So, it’s reasonable to assume ear detection as part of the more ample ear recognition problem (Samuel *et al*., 2011).

Ear detection must deal with several well known challenges (Banafshe Arbab-Zavar and Mark Samuel, 2011; Ni’matus *et al*., 2011). They are usually present in images captured in uncontrolled environments, such as surveillance video systems. These challenges can be attributed to some factors:

a) Feature occlusion: The presence of elements like beards, glasses or hats introduces high variabilit. Ears can also be partially covered by objects or other ears.

b) Ear expression: Ear features also vary greatly because of different ear gestures.

c) Imaging conditions: Different cameras and ambiental conditions can affect the quality of an image, affecting the appearance of an ear. There are some problems closely related to ear detection besides ear feature extraction and ear classification. For instance, ear location is a simplified approach of ear detection. Ear Detection is a concept that includes many sub-problems. Some systems detect and locate ears at the same time, others first perform a detection routine and then, if positive, they try to locate the ear. Then, some tracking algorithms may be needed (Akkermane *et al*., 2005).

3. Ear Biometrics Techniques:

Ear recognition in the field of computer science is related to the “automatic discovery of regularities in data through the use of computer algorithms and with the use of these regularities to take action on it” (Bishop 2006). In other words, regularities or patterns are used to construct models that represent real world circumstances. Then, these models are processed to open the classification of data into different categories or making predictions based on observed data (Alpaydin 2004).

According to Nadler & Smith (1993), the fundamental problem for pattern recognition is to identify an object as belonging to a particular group. Pattern recognition assumes that objects associated with one group are more closely related to one other (i.e., share similar features) than with objects in different groups. Therefore, to determine which group an object belongs in necessitates first identifying the features of a certain object, which is the pattern, and then determining which group those features are most likely to represent, which is recognition. This process may be divided into two fundamental tasks, according to Rettberg *et al*. (2007): the description task generates attributes of an object using feature extraction techniques, and the classification task assigns a group label to the object based on those attributes with a classifier.

These tasks work together to determine the most accurate label for each unidentified object analyzed by the pattern recognition system (Young & Fu 1986).

As a general rule, a biometric system can be regarded as a pattern recognition system, since that process typically involves extracting certain features from available or recently acquired data and comparing those features with a stored template set to determine the identity of an individual (Zhang *et al*. 2009). Research in the use (and improvement) of various biometric methods is extremely valuable for identification, since it is accepted that certain biometric traits are distinct to each individual.

However, Li & Jain (2009) have acknowledged that variations can cause the accuracy of an identification system to drop considerably. Such a decline may be caused by natural processes or presentation issues, noise, and fundamental inadequacies of biometric sensing techniques As a result; Li & Jain (2009) recommend the need to improve current biometric algorithms that enable the identification of variations mentioned and eliminate irrelevant features from the input. The results can be matched with the images in the database in an effective and efficient manner. However, this is no small task since these would require the combination of various techniques to obtain the optimal robustness, performance, and efficiency. According to Li and Jain, such measure is a key step in the biometric algorithm design (Li & Jain 2009).

Over the years, a number of techniques have been used including facial recognition. However, as Chang *et al*. (2003) have stressed, whilst facial recognition is often beneficial for identification purposes (especially in highly structured and controlled settings, e.g., access control, bankcards, mug shots, etc.), it is not foolproof, although the technology is improving all the time. One can change facial features using makeup, altered hairstyle, facial expressions and the variation in lighting, pose and acquisition time, as later confirmed by Boodoo & Subramanian 2007). Based on these limitations therefore, the robustness of a system based solely on facial recognition is questionable. As a new member of non-intrusive biometric recognition technology, ear recognition system has its own advantages (Chang *et al*. 2003). These advantages, according to Lakshmi, Babu & Kiran (2012), are: (a) Ears do not change significantly from the moment in which people reach adult age; (b) Ears' surface is so small to allow working with reduced spatial resolution images; (c) Ears have a uniform distribution of color; (d) They do not change their appearance with the expression of the subject; (e) The effective recognition angle range of about 60° in the horizontal direction when using both ears at one time, which means that it would be twice as face recognition. With ear biometrics, one of the most recent techniques widely used to refer to procedures that compare bits of data to generate identification of an individual called biometric algorithm (Li & Jain 2009, p. 64). Stages include: improving the quality of the original biometric signal, extracting and matching the most important features of a sample, and information blending.

Ear biometrics is a growing field of interest within modern identification systems. The study of features of the ear as useful in identification is not new in itself, It has been useful in forensics for many years, but is relatively new in regards to machine vision approaches to biometrics. For such reason, Arbab-Zavar & Nixon (2011) have chosen that area of research for their recent study.

French criminologist Alphonse Bertillon recognized the biometric potential of human ears as far back in history as the late nineteenth century (Arbab-Zavar & Nixon 2011) when he integrated features of the ear in his "spoken portrait" method for forensic identification. More recently, during the 1980s in the United States, Iannarelli was instrumental in developing a system for describing specific ear features as useful in the identification of individuals (Iannarelli 1989). An ear recognition system is similar to the typical face recognition system and "consists of five components: image acquisition, preprocessing, feature extraction, model training and template matching" (Alvarez, González & Mazorra 2005).

An early attempt at seriously developing an ear biometric system was launched by Burge & Burger (1998) who modelled individual ears with an adjacency graph calculated from a Voronoi diagram of the ear curves. Nevertheless, they did not offer a detailed analysis of their system's biometric potential. Subsequently, therefore, Burge & Burger (2000) finalized a follow-up study that demonstrated ear biometrics can be used for passive identification. In a similar line of research, Hurley *et al*. (2007) used force field feature extraction to chart the ear to "an energy field which highlights 'potential wells' and 'potential channels' as features, achieving a recognition rate of 99.2% on a dataset of 252 images".

Naseem *et al*. (2008) proposed using a process that is successful with face recognition—sparse representation—for ear recognition as well. Similarly, Choras (2005) utilized geometrical properties of ear curves as a basis for identification and recognition. Since part of the problem with using ears for identification relates to pose variation and noise (outside factors that interfere with a clear view of the ear), Bustard & Nixon (2008) recently proposed a robust registration technique for 2D ear images that addressed such problems.

The work of Yan & Bower (2005; 2007) has proven effective in exploiting the 3D structure of the ear with promising results obtained in both instances. For example, Yan & Bowyer (2007) by capturing and segmenting the 3D ear images and using Iterative Closest Point (ICP) registration, they realized a "97.5% recognition rate on a database of 404 individuals" (p. 291). Similarly, Chen & Bhanu (2007) recommended a 3D ear detection and recognition system. They likewise utilized an ICP for recognition, as well as a local surface descriptor, and detailed "96.77 percent rank-1 recognition rate (150 out of 155) on the UCR data set ES and 96.36 percent rank-1 recognition rate (291 out of 302) on the UND data set Collection F" (p. 731). It is still unclear, however, whether 3D techniques for ear biometrics will replace the currently more popular 2D methods (in spite of superior performance with 3D), as using 2D images is consistent with surveillance or other geometric image scenarios.

In another line of research, Alvarez *et al*. (2005) used a modified active contour algorithm and Ovoid model for distinguishing the ear. Likewise, Saleh *et al*. (2006) tested a dataset of ear images using several image-based classifiers and feature-extraction methods. Their results indicated an accuracy rate of 76.5% to 94.1% based on their experiments. Furthermore, Islam *et al*. (2008) proposed an ear detection approach based on the AdaBoost (Adaptive Boosting) algorithm (developed by Freund & Schapire 1997), which is believed to be sensitive to noise and certain outliers in the data. The system developed by Islam *et al* (2007), was qualified with rectangular Haar-like attributes and used a dataset that included a variety of races, sexes, appearances, orientations and illuminations. As cited by Boodoo & Subramanian (2009), The data were collected by cropping and synthesizing from several face image databases. The approach is fully automatic, provides 100% detection while tested with 203 non-occluded images and also works well with some occluded and degraded images.

Boodoo & Subramanian (2009) recognize the benefits as well as the shortcomings of using facial recognition for identification, with imaging problems especially related to lighting, shadows, scale, and translation. In addition, consistent features of the face are often difficult to collect as it is perhaps the most changing features of the body due to issues such as makeup usage, hair styles, facial expressions and facial hair (Boodoo & Subramanian 2009). These researchers scrutinized the use of ear biometrics for authentication and obtained experimental results on a newly created dataset of 420 images. As a result of their research, Boodoo & Subramanian were able to add to the growing evidence that shows ear biometrics can be a superior method of providing identification when compared to facial recognition.

These researchers used ICP matching of the 3D data (which was obtained from a dataset consisting of 404 people), and achieved 97.5% accuracy. ICP-based matching achieved the best performance, in addition to showing high-quality scalability based on the size of the dataset (which included 400 individuals). The goal of this study was to determine ear symmetry as it related to robustness and variability of ear biometrics. Finally, Yan & Bower found that approximately 90% of the populace's right ear and left ear are symmetric.

Also using a 3D ear biometrics system for recognition, Chen & Bhanu (2007) proposed a complete human recognition system that consisted of 3D ear detection, identification, and ear verification. Results showed that the proposed ear recognition system is capable of recognizing ears under pose variations, partial occlusions, and time lapse effects. With multi-sampling and fusion at decision level, this study achieved a recognition rate of 96%. In order to determine the level of success currently experienced in the field, Mir *et al*. (2011) conducted a survey of some of the uni-modal biometrics that we're presently in use (whether in active or limited use) across a range of environments, or still in the process of active research. Specifically, Mir *et al*. Hoped to identify the current and future direction of biometrics in identification.

Choras (2005) proposed a method for identification featuring human ear images, since they are considered to be unchanging over time and could provide more precise features that are available for classification. The method used by Choras was based on placing the center of the new coordinate system in the centroid, making any rotation of the image irrelevant for the purposes of identification, as well as negating the need for translation and scaling, which will allow RST inquiries. The centroid is a key reference point in the feature extraction algorithm, which is divided into two steps. Later, Choras (2007) added additional experiments to expand on the earlier study, and determined that emerging ear biometric methods can be useful in the field of automated computer vision human identification systems. In particular, Choras recommended using multimodal (hybrid) biometrics systems a process that is receiving more attention as time goes on. Due to its advantages over other methods, including facial recognition, ear biometrics could provide additional support to the more well-known methods such as iris, fingerprint or face identification.

Rahman *et al*. (2007) tested an experimental method on 350 samples of 100 persons by day variation taken from various camera viewpoints, and an image size of 250x230". The results obtained by Rahman *et al*. Indicated a successful detection rate of nearly 90 percent, which exceeds the results of both Iannarelli's (1989) and Burge & Burger's (1998) previous research, which were 69 percent and 73 percent, respectively. The ear detection algorithm that was developed by of Rahman *et al*. (2007) is relatively uncomplicated and, consequently, has low computation complexity, making it appropriate for many real-time applications.

Kisku *et al*. (2009) put forward a multi-modal biometric system that included ear biometrics (combined with fingerprints) and featured Scale Invariant Feature Transform (SIFT) descriptor based feature sets taken from fingerprints and ears, and fused them. The results of this study indicated noteworthy upgrading when compared to the individual matching performance of fingerprint and ear biometrics in addition to an existing feature level fusion scheme which have used SIFT as feature descriptor.

Middendorff *et al*. (2007) carried out a review of the existing literature in the field of biometrics related to identification which indicated the use of multi-modal biometrics can improve performance of a recognition system. On the other hand, a consensus does not exist on what features should be used, how they should be acquired, or even how they should be combined. Therefore, Middendorff *et al*. emphasised the importance of considering the type of data to be acquired (e.g. 2D or 3D), the type of recognition algorithm performed on each data element (PCA or ICP), the output of that algorithm (the distance or error metric), the type of fusion to be performed to combine them, and the level at which it should be performed.

The most recent research in ear biometrics includes Zhou *et al*. (2011), who offered a robust technique for 2D ear recognition using color SIFT features. Based on the experiments conducted by the researchers, these methods attain better recognition rates than other methods that are typically viewed as state-of-the-art on the same datasets. Similarly, Rahim *et al*. (2012) presented a novel local features and global features extraction approach to identify ear biometrics. In this study, the ear was divided into specific sections so as to highlight specific local features followed by extraction of the eigenvector from each section. Following this initial process, a number of areas of the ear were identified using ear biometrics. Using a popular classifier, the researchers classified these images using extraction features. In addition, performance analysis was carried out and compared among recognition rates of those features. The proposed region-based features were tested using the well-known benchmark database from the University of Science and Technology Beijing (USTB). Some extracted regions were reported to have low accuracy but, on the whole, the proposed method achieved promising results.

Joshi & Chauhan (2011) offered two approaches to recognize ears from a variety of 2D side face images. The first approach was an edge detection based method, whilst the second method involved template matching. The researchers found that nose-tip detection was extremely important using the edge detection based method, which is based based on distance estimation between the tip of the nose and the ear. In a similar line of study, Jawale & Bhalchandra (2012) endeavored to demonstrate that the ear is a perfect data for passive identification, meaning that it can be applied to provide security in a wide variety of public places and for various security issues. To accomplish this goal, the researchers developed a straightforward two-stage geometric approach for ear recognition. The database used for this study was rather limited, with just of 30 individuals included, but their process was successful in 28 of the subjects.

Finally, Kumar & Wu (2012) presented a similar approach that was completely automated and designed to provide vigorous segmentation of the curved region of interest in the ear, using morphological operators and Fourier descriptors with 2D ear imaging. Kumar & Wu suggested the results of their study provided superior recognition when compared to other popular feature extraction approaches reviewed for their research.

Admittedly, the structure of the ear is still not completely understood and there remain debates regarding whether or not all its discriminant feature can be properly identified. At the same time, as this review of the current literature reveals, various approaches to ear biometric recognition are currently being utilized or in the research stage. Many of the most popular methods today are holistic and focus on general properties and overall appearance of the images (Arbab-Zavar & Nixon 2011). Since the ear is mainly located on a flat surface, the current proposed study is based, in large part, on the pattern established by Arbab-Zavar & Nixon, with the exception that it uses both 2D and 3D images, in order to expand on previous research by including additional aspects of ear recognition that improve on surveillance and other planar-image scenarios. Further, as confirmed by Arbab-Zavar & Nixon (2011), it is beneficial to utilize a model-based approach, in which the ear model is a collection of various ear components.

While the use of 2D imaging appears to be the most popular method used by researchers, the reality is that the performance of most of the current state-of-the-art 2D ear biometric systems tested on a challenging, publicly available dataset (Zhou *et al*. 2011) is somewhat low. For example, methods such as the Principle Component Analysis (PCA) based approach (Zhou *et al*. 2011), as well as feature based approaches, achieved in the order of 70 and 80 percent rank-one recognition rates on a subset of the data, respectively. Whilst other studies have claimed to obtain better rates of recognition (see, e.g., Bustard & Nixon 2008; Choras 2007; Zhang *et al*. 2007), those results were typically obtained from datasets that are viewed as either less complicated or smaller.

4. Taxonomy of Ear Recognition:

More specifically, ear recognition techniques fall in four categories, hybrid based methods, model based methods, and feature based methods and holistic method as illustrated in Figure 2.

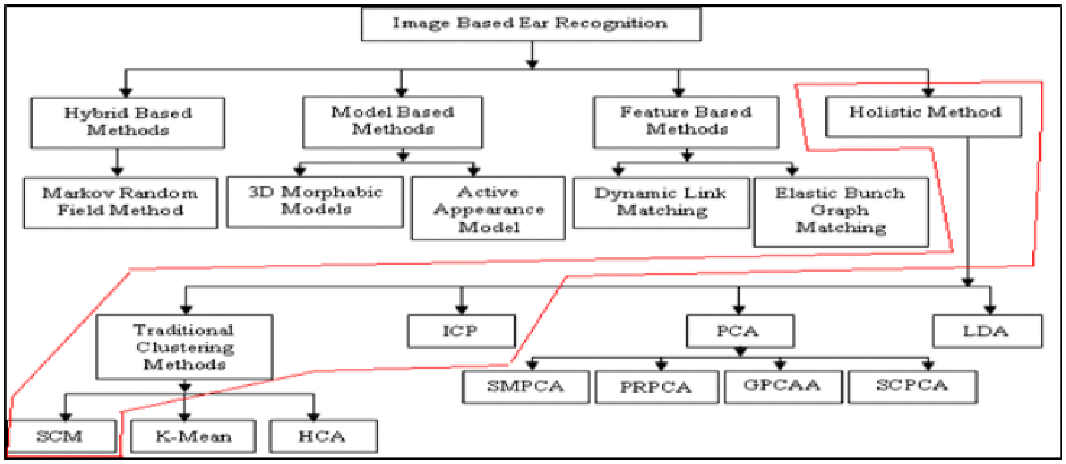

Fig. 2: Taxonomy of Ear Recognition Approaches.

It's not easy to give taxonomy of ear detection methods. There isn't a globally accepted grouping criterion (Hui *et al*., 2009). They usually mix and overlap. In this section, ear detection, ear feature extraction and ear classification approaches is presented. The red shadow part is described the approach that being used in this research (Akkermane *et al*., 2005).

The templates in appearance-based methods learn from the examples in the ear images. In general, appearance-based methods rely on techniques from statistical analysis and machine learning to find the relevant characteristics of ear images. Some appearance-based methods such as Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), Iterative Closest Point (ICP) and Traditional Clustering Method work in a probabilistic network. An image or feature vector is a random variable with some probability of belonging to an ear or not. Appearance-based ear recognition algorithms use a wide variety of classification methods. Sometimes two or more classifiers are combined to achieve better results. On the other hand, most model-based algorithms match the samples with the model or template (Akkermane *et al*., 2005; Hui *et al*., 2009).

In this paper, a full description analysis algorithm is clarified on the USTB ear database (Lu and Plataniotis 2002) which contains ear images with rotation variations and Indian Institute of Technology Kanpur (IITK Kanpur).

Two different databases will be utilized in this research, one from the University of Science and Technology Beijing (USTB) database and another, Indian Institute of Technology, Kanpur (IIT Kanpur) database, consist at least of 500 images from each database. Hence, a minimum of 1000 subjects will be incorporated into the research (50 images from the data set of I, 300 images from Data set 2 and 180 images from Data set 3 from both IIT Kanpur and USTB databases).

To show the rotation (pose) and scale invariance of the proposed technique, Data Set 2 of IITK and USTB databases is used and large number is needed. Accuracy for Data Set 1 is the highest as it contains frontal ear images so small numbers will involve.

In addition , The proposed technique has also detected ears successfully in the images of Data Set 3 of IITK and USTB databases (where images contain out-of-plane rotations) even for the extreme poses (-40 and +40 degrees).

A. Iitk Kanpur:

IIT Kanpur (IITK) database is composed of two data sets. Data Set 1 contains 801 side face images collected from 190 subjects. Number of images acquired from an individual varies from 2 to 10. Figure 3 shows few sample images from Data Set 1. Data Set2 consists of 801 side face images collected from 89 individuals. For each subject, 9images are captured by considering three rotations and three scales for each rotation.Images of Data Set 2 consist of frontal view of the ears captured at three positions,first when a person is looking straight, second when he/she is looking approximately 20down and third when he/she is looking approximately 20 up. At all these positions, images are captured at 3 different scales by positioning the camera at a distance of approximately 1 meter and setting up the digital zoom of the camera at 1:7x, 2:6x and3:3x. Figure 3 shows 9 images from Data Set 2 for an individual. The purpose of the use of multiple data sets is to show the robustness of the proposed approach. IITK Data Set 1 provides frontal ear images while IITK Data Set 2 provides challenging images which are affected by scaling and rotation (Surya Prakash & Phalguni Gupta 2012).

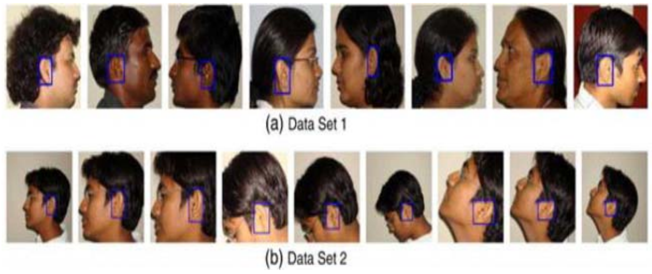

Fig. 3: Some examples of the Image IITK database.

B. Ustb Ear Imagedatabases:

The USTB ear image database is supporting academic research of ear image as a main purpose. USTB database consists to two main databases as I, II and III. The total number of database I image volunteers is 60. In which every volunteer is photographed three different images. They are normal frontal image, frontal image with trivial angle rotation and image under different lighting condition. Each of them has 256 gray scales. Images had already experienced rotation and shearing, but they were without illumination compensation (Bay *et al*. 2008). The total number of database II image volunteers is 77. In which every volunteer is photographed four images. They are profile image, two images with angle variation and one with illumination variation. Each image is 24-bit true color image and 300*400 pixels. The first image and the fourth one are both profile image but under different lighting. The second and the third one have the same illumination condition with the first while they have separately rotated +30 degree and -30 degree with the first one. Thus, the main purpose of the image database is to support the research about ear recognition under illumination variations and angle variations (Bay *et al*. 2008).

Fig. 4: Some examples of the Image USTB Database1.

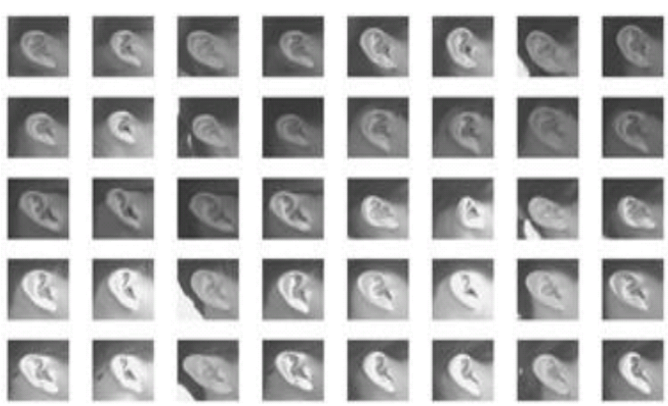

Fig. 5: Examples of the USTB Database II Image.

The total number of database III image volunteers is 79. In which every All images are right side profile full image which are photographed with a color CCD camera under the white background and constant lighting. The distance between camera and subject is 1.5 meters. The resolution of the image is 768*576, 24-bit true color. Defines the angle when CCD camera is perpendicular to ear as 0 degrees, which we call profile side as shown in figure 4 and 5.

Table 1: Highlighted the summary of existing ear recognition systems, methods, algorithms and frameworks.

Author/s	**Key Issue**	**Key Feature**	**Contribution**	**Limitation**
Alvarez, L., González, E. & Mazorra, L. 2005. Fitting ear contour using an ovoid model. In *Proceedings of International Carnahan Conference on Security Technology*, pp. 145-148. Arbab-Zavar, B. & Nixon, M.S. 2011. On guided model-based analysis for ear biometrics. *Computer Vision and Image Understanding* 115: 487-502. Boodoo, N.B. & Subramanian, R.K. 2009. Robust Multi biometric Recognition Using Face and Ear Images. *International Journal of Computer Science and Information Security* 6(2): 164-169. Chen, H. & Bhanu, B. 2007. Human Ear Recognition in 3D. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 29(4): 718-737. Jawale, J.B. & Bhalchandra, A.S. 2012. The Human Identification System Using Multiple Geometrical Feature Extraction of Ear–An Innovative Approach. *International Journal of Emerging Technology and Advanced Engineering* 2(3): 662-666. Joshi, K.V. & Chauhan, N.C. 2011. *Edge Detection and Template Matching Approaches for Human Ear Detection*. International Conference on Intelligent Systems and Data Processing (ICISD). Special Issue published by International Journal of Computer Applications. Kisku, D.R., Gupta, P. & Sing, J.K. 2009. Feature Level Fusion of	This study combined geodesic active contours and a new ovoid model, was developed, which can be used to compare ears in an independent way of the ear location and size. Study used a hybrid model derived by a stochastic clustering on a set of scale invariant features of a training set and a wavelet-based analysis with a specific aim of capturing information in the ear's boundary structures, which can augment discriminant variability. This study investigates the use of ear as a biometric for authentication and shows experimental results obtained on a newly created dataset of 420 images. The study proposed a complete human recognition system using 3D ear biometrics. The system consists of 3D ear detection, 3D ear identification, and 3D ear verification. Multiple geometrical feature extraction (such as shape, Euclidian distances of side of a triangle and angles of a triangle as a feature vector) of ear based method to identify a person using ear biometrics has been proposed. The study presented two approaches to detect ear from 2D side face images. One is edge detection based method and the other is template matching method. This paper presents a multimodal biometric system of fingerprint and	This paper proposed a new way to fit the contour of an ear in an image by combining snake techniques and a new ovoid model. Sought to present a thorough evaluation of performance in occlusion, using a robust PCA for comparison purposes by guiding a model-based analysis via anatomical knowledge. The purpose of the proposed paper is to investigate whether the integration of face and ear biometrics can achieve higher performance that may not be possible using a single biometric indicator alone. Ear biometrics has the potential to be used in the real-world applications to identify/authenticate humans by their ears. It can be used in both the low and high security applications and in combination with other biometrics such as face. Attempted to prove that the human ear is a perfect data for passive person identification, which can be applied to provide security in the public places. The purpose of the paper is to compare the results of both the presented methods. Purpose was to show that ears have several advantages over facial features such as uniform distributions of intensity and spatial resolution, and less variability with expressions and orientation of the face Purpose was to fill the gap in efforts to	The study developed some algorithms to estimate automatically the ovoid which better fit an ear contour using an euclidean distance criterion. The study's hybrid method obtains a better performance than RPCA on test set. With multi-sampling and fusion at decision level, a recognition rate of 96 % was obtained. Results showed that the proposed ear recognition system is capable of recognising ears under pose variations, partial occlusions, and time lapse effects. A simple two stage geometric approach for ear recognition has been implemented. Data of 30 people tests have been conducted, successful results were found for 28 subjects. The results concluded that for edge detection based method the nose tip detection is very important because in this method ear detection is based on distance estimation between nose tip and ear. The results show significant improvements over the individual matching performance of fingerprint and ear biometrics as well as an existing feature level fusion scheme which have used SIFT as feature descriptor. The experimental results suggest the superiority of the proposed approach over the other popular feature extraction approach considered in this work. Researchers have already come up with various approaches which drastically differ from each other in	Subject to the limitations in ear analysis application such as occlusion by hair, use of hat or earring. Studies were under the whole ear is visible. The helix and the antihelix were under-represented the model. RPCA performance degrades in one test set. Recognises the need for larger datasets of ear images for more accurate estimate of the recognition performance and acknowledges that pose variation and lighting changes potentially alter visual characteristics of the structure. Require further testing and enhancement under uncontrolled environment for potential surveillance application. The proposed representation for surface matching consisting of the ear helix/antihelix and the local surface patch (LSP) are less sensitive to pose variations. Errors occur for poor images of the outer shape of the ear that may result to the total failure of the whole approach. An alternative test to check the integrity of the image with different max lines in different angles maybe used for image integrity testing. Detection performance is highly dependent on the template. It has has to be recreated for different datasets otherwise it degrades

Biometrics Cues: Human Identification with Doddington's Caricature, pp. 157-164. In Slezak et al. *Communications in Computer and Information Science*. Springer: Warsaw.	ear biometrics. Scale Invariant Feature Transform (SIFT) descriptor based feature sets extracted from fingerprint and ear are fused.	investigate the human ear for personal authentication despite its significant role in forensic science.	terms of acquisition, raw data interpretation and feature extraction.	the performance The method used fails if ears are heavily occluded by hair.
Kumar, A. & Wu, C. 2012. Automated human identification using ear imaging. *Pattern Recognition* 45(3): 956-968.	This study presented a completely automated approach for the robust segmentation of curved region of interest using morphological operators and Fourier descriptors using 2d ear imaging.	Purpose was to identify the current and future direction of biometrics in identification.	Experiments indicated that the study's method can achieve better recognition rates than the state-of-the-art methods applied on the same datasets.	Matching scores are generated using wolf-lamb user-dependent feature weighting scheme. Recognition accuracy of 96.27% and 95.93% is limited to 125 and 221 subjects. Needs further testing for marks above the respective number of samples.
Mir, A.H., Rubab, S. & Jhat, Z.A. 2011. Biometrics Verification: a Literature Survey. *International Journal of Computing and ICT Research* 5(2): 67-80.	Paper conducted a survey of some of the unimodal biometrics that are either currently in use across a range of environments or those still in limited use or under evelopment, or still in the research realm.	This study, as with most biometrics research, was strongly motivated by an increase in application demand.		Findings suggest that the amount of applications employing unimodal biometric systems is quite limited. Thus, The future of biometrics can be anchored on multimodal biometric systems.
Zhou, J., Cadavid, S. & Abdel-Mottaleb, M. 2011. Exploiting color SIFT features for 2D ear recognition. *18th IEEE International Conference on Image Processing*, pp. 553-556.	This paper presented a robust method for 2D ear recognition using color SIFT features.			Neither time lapse nor lighting variations between the gallery and probe images is presented in the dataset. Untested for videoclips captured in an outdoor environment with uncontrolled lighting conditions.

5. Research Gap:

The most common gap observed in the literature refers to the need for testing the involved processes and applications by incorporating larger data sets or more images within the available datasets of ear images, in addition, a more accurate estimate of the recognition performance could be obtained by adding additional images to the structure of the ear and potential variations such as pose variation and lighting changes to test their performance suited for surveillance applications.

In effect, the purpose of the research will be to determine to what extent variations in pose (including differing angulations, and distances) to obtain a positive identification using ear biometrics with field feature extractions.

Will be combine an Iterative Closest Point (ICP) algorithm, which is widely used for 3D shape matching, with the stochastic clustering algorithm used by Arbab-Zavar & Nixon to generate a new contribution to the field of research. Specifically, the IIT Kanpur database, consisting of the side faces with variable sizes (A method that under a number of human different ages is therefore, needed), rotations and shapes, and the benchmark database from the University of Science and Technology Beijing (USTB) will be utilized.

Lastly, this research endeavors to fill the research gap mentioned in the preceding section. An attempt will hence be made to involve larger datasets greater than any number committed in the extant literature. The study will address the other gaps and present an outline of empirically-driven recommendations for future applications and research efforts.

6. Conclusion and Remarks:

The major advantages of ear identification over face recognition modeling is mainly due to the fact that the mathematical functions correspond to the image reality of the viewing geometry and take into account all the mismatches generated in the image while face model parameters do not have any physical meaning.. It will be inspiring to discover which features that are the furthermost significant in determining ear recognition. Hereafter, it will be able to weigh them properly in the process with different types of features. Classification is based on the MNN output between the input image feature, and all the images from the database. It will follow by testing some new geometrical parameters recounting shapes of ear contours and compare their effectiveness in ear recognition.

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