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Profile Silhouette and Gender Recognition

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ABSTRACT

Security issues seem to be one of the most important problems of contemporary computer science. One of the most important branches of security is identification users. In this paper we present the basics of using ear biometric for identification and then using ear we will classify gender. For this purpose we use statistical technique principal component analysis (PCA). We used one of the biometric human features (ear structure) for identification. We employ profile images for identification from ear and gender recognition has based on ear and eyebrow location in men and women.

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INTRODUCTION

Measurement of physiological or behavioral characteristics of an individual's is called biometrics. Major biometric features include fingerprints, palm-knowledge, retina, iris, hand and facial structure, voice, teeth, walking and speech, ear smell, handwriting, keyboard text, signature, hand veins shape and DNA. (Nabiyev, 2009) Biometric approaches are generally divided into two main branches, depending on the features. This is in order to identification and to claims verifying.

As there is an ever-growing need to automatically authenticate individuals, biometrics has been an active field of research over the course of the last decade. Traditional means of automatic recognition, such as passwords or ID cards, can be stolen, faked, or forgotten. Biometric characteristics, on the other hand, are universal, unique, permanent, and measurable.

The characteristic appearance of the human outer ear (or pinna) is formed by the outer helix, the antihelix, the lobe; the tragus, the antitragus, and the concha (see Figure 1). The numerous ridges and valleys on the outer ear's surface serve as acoustic resonators. For low frequencies the pinna reflects the acoustic signal towards the ear canal. For high frequencies it reflects the sound waves and causes neighbouring frequencies to be dropped. Furthermore the outer ear enables humans to perceive the origin a sound.

The shape of the outer ear evolves during the embryonic state from six growth nodules. Its structure, therefore, is not completely random, but still subject to cell segmentation. The influence of random factors on the ear's appearance can best be observed by comparing the left and the right ear of the same person. Even though the left and the right ear show some similarities, they are not symmetric (Abaza *et al*. 2010). The shape of the outer ear has long been recognized as a valuable means for personal identification by criminal investigators. The French criminologist Alphonse Bertillon was the first to become aware of the potential use for human identification through ears, more than a century ago. In his studies regarding personal recognition using the outer ear in 1906, Richard Imhofer needed only four different characteristics to distinguish between 500 different ears (Nabiyev, 2009). Starting in 1949, the American police officer Alfred Iannarelli conducted the first large scale study on the discriminative potential of the outer ear. He collected more than 10 000 ear images and determined 12 characteristics needed to unambiguously identify a person (Iannarelli, 1989). Iannarelli also conducted studies on twins and triplets, discovering that ears are even unique among genetically identical persons. Even though Iannarelli's work lacks a complex theoretical basis, it is commonly believed that the shape of the outer ear is unique. The studies in (Meijerman *et al*.,2004) and (singh *et al*.,2009) show that all ears of the investigated databases posses individual characteristics, which can be used for distinguishing between them.

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Because of the lack of a sufficiently large ear database, these studies can only be seen as hints, not evidence, for the outer ear's uniqueness.

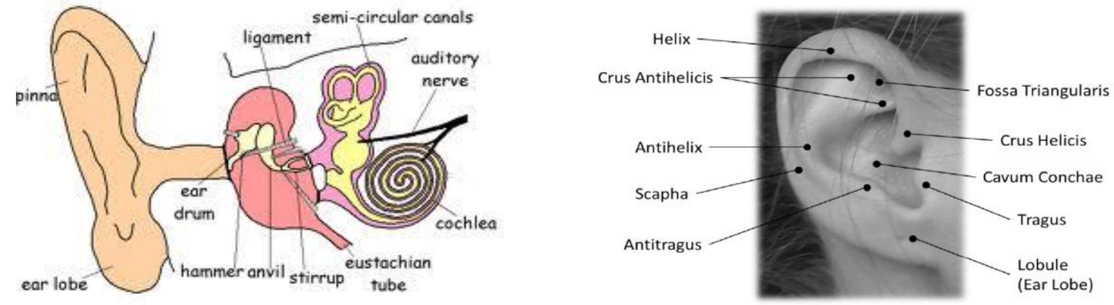

Fig. 1: Ear structure and Characteristics of the human ear the German criminal police uses for personal identification of suspects

Research about the time-related changes in the appearance of the outer ear has shown, that the ear changes slightly in size when a person ages (Sforza *et al*., 2009) (Meijerman *et al*. , 2007). This is explained by the fact that with ageing the microscopic structure of the ear cartilage changes, which reduces the skin elasticity. A first study on the effect of short periods of time on ear recognition (Ibrahim *et al*., 2011) shows that the recognition rate is not affected by ageing. It must, however, be mentioned that the largest time elapsing difference in this experiment was only 10 months, and it therefore is still subject to further research whether time has a critical effect on biometric ear recognition systems or not.

The ear can easily be captured from a distance, even if the subject is not fully cooperative. This makes ear recognition especially interesting for smart surveillance tasks and for forensic image analysis. Nowadays the observation of characteristics is a standard technique in forensic investigation and has been used as evidence in hundreds of cases. The strength of this evidence has, however, also been called into question by courts in the Netherlands (Hoogstrate *et al*., 2001). In order to study the strength of ear prints as evidence, the Forensic Ear identification Project (FearID) was initiated by nine institutes from Italy, the UK, and the Netherlands in 2006. In their test system, they measured an Equal Error Rate (EER) of 4% and came to the conclusion that ear prints can be used as evidence in a semi-automated system (Aberink *et al*., 2007). The German criminal police use the physical properties of the ear in connection with other appearance-based properties to collect evidence for the identity of suspects from surveillance camera images. Figure 1 illustrates the most important elements and landmarks of the outer ear, which are used by the German BKA for manual identification of suspects. (Anika *et al*., 2011) Extend existing surveys on ear biometrics. Their work covers the history of ear biometrics, a selection of available databases and a review of 2D and 3D ear recognition systems.

In the following section we review some of ear biometric methods. In section 3, we illustrate PCA algorithms and PCA mathematical modelling in face recognition. In section 4 we present proposed way for ear region detection in profile face for identification and gender recognition. Experimental results summarized in section 5. Finally, we conclude by some future work direction.

Ear Biometric Method:

There are at least three methods for ear identification: (i) taking a photo of an ear, (ii) taking “earmarks” by pushing ear against a flat glass and (iii) taking thermogram pictures of the ear. The most interesting parts of the ear are the outer ear and ear lope, but the whole ear structure and shape is used.

Taking photo of the ear is the most commonly used method in research. The photo is taken and it is combined with previous taken photos for identifying a person. The earmarks are used mainly in crime solving. Even though some judgments are made based on the earmarks, currently they are not accepted in courts. The thermogram pictures could be one solution for solving the problem with e.g. hair of hat.

A. Photo comparison:

Alfred Iannarelli has made two large-scale ear identification studies in 1989. In the first study there were over 10,000 ears drawn from a randomly selected sample in California. The second study was for researching identical and non-identical twins. These cases support the hypothesis about ear uniqueness. Even the identical twins had similar, but not identical, ear physiological features.

Alfred Iannarelli had been working 30 years as deputy sheriff in Alameda County, California, as the chief of the campus police at California State University at Hayward, and in several other law enforcement positions. He became interested in ears in 1948 and over the next 14 years classified about 7,000 ears from photographs. The first version of the book describing his classification method was published 1964. The second edition was published in 1989. Iannarelli does not have academic background for his studies.

Alfred Iannarelli has created a 12 measurement “Iannarelli System” (see figure 2). He uses the right ear of people, specially aligns and normalizes the photographs. To normalize the pictures, they are enlarged until they fit to the predefined easel. After that the measurements are taken directly from the photographs. The distance between each of the numbered areas (figure 2) is measured and assigned an integer distance value. The identification consists of the 12 measurements and the information about sex and race. Burge and Burger (1998) comment that the method is not suitable for machine vision because of the difficulty of localizing the anatomical points. If the first point is not defined accurately, none of the measurements are useful. Iannarelli himself has also recognized this weakness of his system.

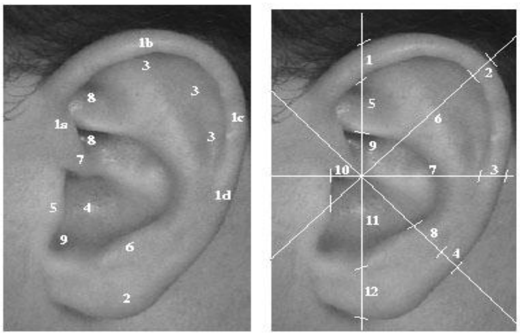

Fig. 2: (a) Anatomy, (b) Measurements. (a) 1 Helix Rim, 2 Lobule, 3 Antihelix, 4 Concha, 5 Tragus, 6 Antitragus, 7 Crus of Helix, 8 Triangular Fossa, 9 Incisure Intertragica. (b) The locations of the anthropometric measurements used in the “Iannarelli System”.

After Iannarelli’s classification there have become different, more scientific methods for ear identification. Victor et al. (2002) and Chang et al. (2003) have used principal component analysis (PCA) and FERET evaluation protocol for their research about the ears.

Moreno et al. (1999) presented multiple identification method, which combines the results from several neural classifiers using feature outer ear points, information obtained from ear shape and wrinkles, and macro features extracted by compression network. They also introduce three different classification techniques for outer ear or auricle identifying.

Burge and Burger (1998, 2000) have researched automating ear biometrics with Voronoi diagram of its curve segments. They have used a novel graph matching based algorithm for authentication, which takes into account the possible error curves, which can be caused by e.g. lightning, shadowing and occlusion.

Hurley, Nixon and Carter (2000a, 2000b) have used force field transformations for ear recognition. The image is treated as an array of Gaussian attractors that act as the source of the force field. According to the researchers this feature extraction technique is robust and reliable and it possesses good noise tolerance.

B. Earmarks:

Ear identification can be done from photographs or from video. There is another possibility: the ear can be pressed against some material, e.g. glass, and the ‘earmark’ can be used as a biometric. This has been used in crime solving. In England four delinquents have been judged between 1996-1998 by using only the earmarks (Bamber, 2001). However in the Netherlands the court decided that the earmarks are not reliable enough for judging (Forensic-Evidence News, 2000). The Dutch found out that the earmarks usually doesn’t have enough details for reliable identification. Also when there are no dependable proofs that ears are unique, it was decided that ear identification cannot be used as evidence.

C. Thermogram pictures:

In case the ear is partially occluded by hair the hair can be masked out of the image by using thermogram pictures (see figure 3). In the thermogram pictures different colours and textures are used to find different parts of hear. In the figure 3 the subject’s hair is between 27.2 and 29.7 degrees Celsius while the outer ear areas range from 30.0 to 37.2 degrees Celsius. The ear is quite easy to detect and localizable using thermogram imagery by searching high temperature areas (Nabiyev, 2009).

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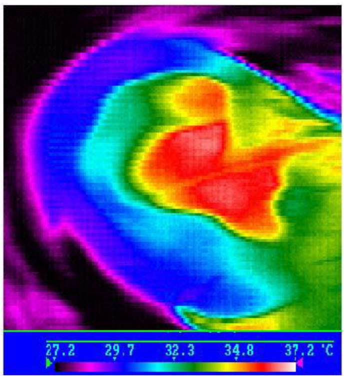

Fig. 3: Thermogram of an ear. Image provided by Brent Griffith, Infrared Thermography Laboratory, Lawrence Berkeley, National Laboratory.

PCA Algorithm:

A number of algorithms have been proposed to extract the first p principal components from d dimensional (d>p) stochastic process with the help of a neural network. These algorithms are advantageous in adapting online to the data and thus no explicit computation of the covariance matrix and its eigenvalue decomposition is necessary. In local Hebbian type learning algorithms, the modification of the Ith row of the Weight matrix W between input and output layer depends only on the Ith output unit and the input. Due to this locality it has been argued that these algorithms are “biologically plausible”. In such local algorithms have been analyzed and it was shown that only one part of these algorithms, the asymmetric algorithms, where there is a hierarchical connection between the output units, can lead to asymptotically stable equilibrium, whereas algorithms with a symmetric connection in the output layer is not asymptotically stable. Thus, it was concluded that asymmetric algorithms should be preferred, although they disallow “competition” and lack symmetry.

A. PCA Mathematical Modelling:

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let’s suppose we have M vectors of size N (= rows of image×columns of image) representing a set of sampled images. pj’s represent the pixel values.

$$xi = [p1 \ \dots\dots\dots\dots pn\,]\ T \ , \qquad i = 1 \dots\dots\dots . M$$

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.

$$m = \frac{1}{m}\sum_{k=1}^{m} Xi$$

And let w_i be defined as mean centered image

$$wi = xi - m$$

Our goal is to find a set of ei’s which have the largest possible projection onto each of the w_i’s. We wish to find a set of M orthonormal vectors ei for which the quantity is maximized with the orthonormality constraint

$$\lambda i = \frac{1}{m} + \sum_{n=1}^{m} (ei^T Wn)^2$$

$$e_i^T e_k = \ \delta ik$$

It has been shown that the ei’s and ¸i’s are given by the eigenvectors and eigenvalues of the covariance matrix

$$W = WW^T$$

Where W is a matrix composed of the column vectors wi placed side by side. The size of C is N × N which could be enormous. For example, images of size 64×64 create the covariance matrix of size 4096× 4096. It is not practical to solve for the eigenvectors of C directly. A common theorem in linear algebra states that the vectors ei and scalars ʎ i can be obtained by solving for the eigenvectors and eigenvalues of the M ×M matrix $W^T W$. Let di and μi be the eigenvectors and eigenvalues of $W^T W$ respectively.

$$W^T W . di = \mu idi$$

By multiplying left to both sides by W

$$WW^T (Wdi) \ = \mu i(Wdi)$$

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Which means that the first M -1 eigenvectors ei and eigenvalue ʎ i of WWT are given by Wdi and μi respectively. Wdi needs to be normalized in order to be equal to ei. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix cannot exceed M - 1 (The -1 come from the subtraction of the mean vector m). The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions.

A facial image can be projected onto M'' (<< M) dimensions by computing

$$\Omega = [v1v2............v^{m'}]^T$$

Where vi = eTiwi, vi is the Ith coordinate of the facial image in the new space, which came to be the principal component. The vectors ei are also images, so called, eigenimages, or eigenfaces in our case. They can be viewed as images and indeed look like faces. So Ω describes the contribution of each eigenfaces in representing the facial image by treating the eigenfaces as a basis set for facial images. The simplest method for determining which face class provides the best description of an input facial image is to find the face class k that minimizes the Euclidean distance

Ek =||((Ω - ΩK))||

Where ΩK is a vector describing the k^{Th} face class? If Ek is less than some predefined threshold θK a face is classified as belonging to the class k (Pallavi *et al*., 2013).

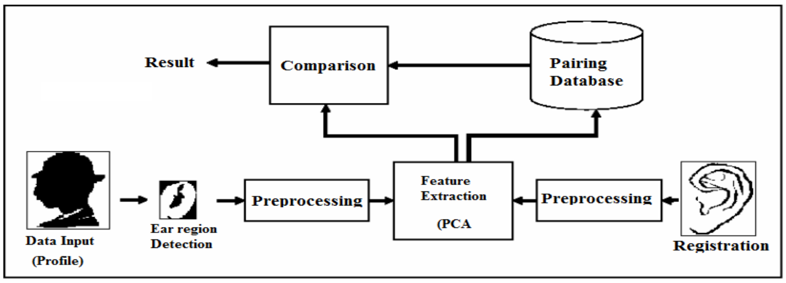

Fig. 4: Ear biometric recognition system

Ear Region Recognition in Profile:

In this work, profile face image or ear region image is getting as input image. In profile face, image ear region estimated by profile faces canons. And then after review, ear region specified as a frame. Obtained gray ear registered by mask and then perform recognition processes. Ear statistical approach features obtained by principal component analysis (PCA) for recognition processes. Figure 4 shows ear's biometric proposed general structure.

A. Profile Faces From Canons:

For identification first ear region should be detected from profile faces. In general the relation between man and women faces are same. Of course don't forget that these relations may be having difference for various humans. Faces have been seen from profile, the height and length of it is three and half unit. So the human's head from profile are as a square. If draw a straight line from lips to up, this line passes from eye accuracy. Straight line passes from end of nose tangent low lip. Upper lip and small section of brow stand out of line. Chin and nostril state in both side of this vertical line.

If distance between chin to eye is called A, distance between eye to end of ear is same distance too. If distance between lips to eye is called B, distance between eye and first of ear is B too. Distance between eye and outset of ear equal to distance between extremity of ear and end of head; but may be this distance be more than real size. Figure 5 show a profile image of man and women.

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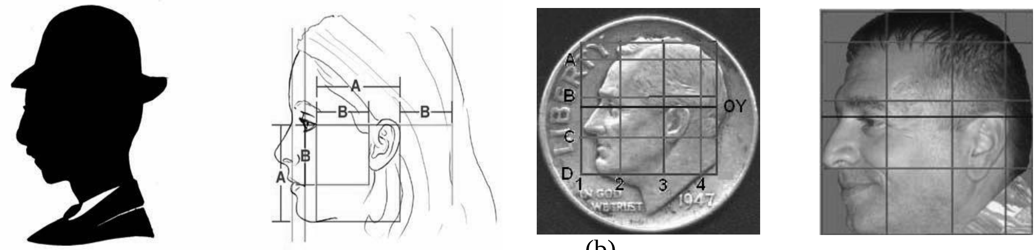

(a) (b)

Fig. 5: (a) Profile image of man (b) Profile image from canons

If evaluate profile image of human head, is achieved (b).the profile image of human head constitution same selection. Here distance between A-B, B-C, C-D, 1-2, 2-3and 3-4 are same. OY line divides the head of human for two same parts. Of course this division valid for normal human's head. Generally these evaluations don't give a quite right result.

B. Preprocessing:

First, in preprocessing image transform to gray format. In this transformation red, green and blue portions of each pixel multiply respectively 0.11, 0.59 and 0.3 in order to determine its value. After get the gray images, applied the Sobel's edges detection algorithms in order to determine edges. After this work, normalized value of each pixel because may be negative the value of some pixels or be more than 255.this is necessary the value of them should be between 0-255.

C. Ear Region Finding:

For profile recognition suggested different methods. In this paper used profile face canons for finding ear region in profile images. First for determine ear region we should determined nose, chin, lip, under of nose, eye and eyebrow. Furthermore situation of profile images should be same and constant. So, in this paper recognition is based on pixel, finding nose require a search. Based on evaluation, finding tip of nose is in middle of rang. For finding chin, we used profile face canons, too. The situation of input images can be different. This difference is causing the error in identification. For avoidance this error we should fix angle of view. For this purpose in all of images we are considered angle between two points of nose and chin 18. Rotate the image have not this condition and transform it for above state. As the profile image of human shows, ear region were in second and third part of Stretches tip of nose and height of ear is limited to eyebrow and under of nose state. According to detected region ear will be selected. Figure 6 show a simple of different ears of ear database.

D. Gender Recognition:

After we use profile face canons for finding ear region, now find helix ear region. As we use pixel change for this work. Top of ear frame section shows helix that having maximum changes. Now we will draw a horizontal tangent line above helix parallel of divided lines in section b of figure 4 that is called OY line.

According to men's eyebrow is thicker that women eyebrow and this is one of the men's and women's differences. So eyebrow ornamentation causes thinner than real state in women. Of course this sentence may be does not true in all of the men and women. If study OY line for different images, we will see that OY line falls in under eyebrow region in female's images and falls in above eyebrow region in male's images.

Fig. 6: Ear samples from the database

Discussion:

Ear information was got from profile images of FERET profile face database that sizes is 256×384. For this purpose we used MATLAB software and profile face from canons. Ear image that size 50×60, analyzed by PCA and it's Eigen vector and Eigen Value computed then ear image will be studied with ear database. According to calculated Eigen vector by PCA. This study is based on Euclidian distance. Threshold was selected 2500 for Euclidean distance. The system trained by 35 data and tested with 15 Ear data. Identification experiments show correct results 80%.

Next phase of experiments is for gender recognition of profile image based on localized features of ear and eyebrow. Experiments done for selected profile images of FERET database that there size is 256×384. Experiments results show that 87.5% of gender recognition system determined male and female correctly.

Conclusion:

In this work used one of the biometric human features (ear structure) for identification. We employ profile images for identification from ear. In profile images Ear region determined by anthropometric principal automatically. We used principal component analysis (PCA) for feature extraction in determined region after mask operation and perform identification by ear using Euclidean distance then complete gender recognition anthropometric principal and human feature. This gender recognition has based on ear and eyebrow location in men and women. In future work, we will perform profile image identification by using curves of brow, nose, lip and chin geometrically.

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