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A Review on Features Extraction of Two Dimensional Ear Images and Occlusion Challenge

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ABSTRACT: In this paper, person identification studying recently has received significant attention. There are several reasons for this trend of ear recognition. Ear recognition is biometric and non-contact way like face recognition that doesn't suffer people. Also ears can be used to identify people in surveillance images where the face may be completely occluded. Furthermore ear appearance changes a little by the age. But in reality ear image may be occluded little or completely. Therefore these occlusions that may occur during the identification finally can lead to a decline in efficiency of person identification. We provide a literature review of recent research in ear recognition and detection. Besides a review in literature this study can be an exploit for researchers who might use a new approach. The problem of identifications such as occlusion of ear image and their countermeasure to solve them will be studied in this paper.

KEYWORDS: Human recognition, two dimensional, ear images, occlusion, feature extraction

I.INTRODUCTION

Person identification using ear biometrics has drown significant attention of many researchers recently. Ear biometric has the advantage of non-intrusive acquisition in a non-controlled environment. But always there is a compromise between the non-intrusive image and the quality of image environment. Generally biometric is acquired by the surveillance camera instead of controlled obstacle. Recent research is focused on developing a vigorous biometric system that can obtain a high rate recognition under every personal and environment condition. The structure of the ear due to its geometric shape that is individual is one of that biometrics. This can be an individuality of a person when his/her face is seen in the image. This individuality is also true for twins. Ear biometric will has a high acceptance between its users because of its non-intrusive and passive nature. Ear biometric performance may be destructed from natural condition like occlusion, lightening and different gestures of people. Since ear may be occluded partially or completely by hair, hat or scarf, necessary information which is lost by occlusion cannot be retrieved as using rectification techniques to regain some part of information which is lost by lightening or different position. We study the literature and research conducted in ear biometric. The goals of this study is:

1. An introduction of ear biometric system processes and available database which is used in many papers to study person identification from two dimension ear image.

2. Study 20 papers published from 2003 to 2016.

3. State the occlusion problem in person identification by using ear biometric.

This paper is included: 2.presented a brief of ear biometric system. 3. Present two useful and available database for research. 4. A survey of methods of extraction of individuality. 5. Present the main problem of person identification using ear image

II.EAR BIOMETRIC SYSTEMS

An ear biometric system may be viewed as a typical recognition pattern when the input image is reduced to a set of identification features and subsequently compare to a set of features of other images for identification. Ear recognition



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

can be accomplished using 2d images and 3d points that is captured from 3d space of ear surface. Ear recognition system process is as following:

A.EAR DETECTION

The first stage of ear recognition is to localize an ear in an image. Rectangular boundary is typically used to indicate place of ear in an extended space of a given image. Since many errors in this stage can spoil the utility of biometric system, this stage is a critical part of ear biometric system.

B.EAR NORMALIZATION

In this stage the detected ear is subjected to improve the image. Furthermore ear image may be subjected to select the geometric and photometric relations to facilitate the extraction of features and matching.

C.FEATURE EXTRACTION

While segmented ear can be used directly for matching stage, the system mostly extract a set of typical features for ear. Feature extractions referred to extraction of features from the segmented ear which reduced it to a Mathematical model. In fact this is a summarized of privileged information.

D.MATCHING THE FEATURE

Extracted feature in the previous stage can be used to compare to stored feature in data base and in order to identify the input image. The simplest way of matching is to provide a match score by comparing the set of features. Matching score is referred to the similarities between two ear images.

E.DECISION

In this stage by using matching score provided in matching stage final verification decision is made. The output of this stage is in the form of a "yes" or "no" to accept or not accept the input image, which is sequencing referred to the original and fake person. Therefore the output of identification system is a list of identification operations with their matching score.

III.PRESENTING TWO TYPES OF DATABASE

Test and development of a robust ear recognition algorithms require databases that is controlled from factors like lightening and position. In this section we present two commonly used database for ear recognition that have been tested and concluded in many surveys

A. USTB DATABASE

Database collected by the University of Science and technology of Beijing and is available for the researchers.

- Image databaseI: included 180 images of right ear from 60 different people.3 image was taken of everyone, included a normal image and images with rotation and different lightening condition.
- Image databaseII: included 308 images of 77 people, with the view of 0° and with the angle of 30° and -30° and with the similar lightening condition.
- Image databaseIII: in this database there are images of face and ear both together included 79 different people. Two image was taken from everyone with different rotate angle of 0°, 5°, 10°, 15°, 20°, 25°, 30°, 35°, 40°, 45°, 50°, and 60°. These images have partial, trivial, and regular occlusion. Sample images is seen in figure .1 Image databaseIV: using CCD camera to taking images of ear and face together with interval of 15° between them. The database consists of 500 different subjects.



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016



Fig .1Samples image of USTB III

B.UND DATABASE

Collection F: including 464 half faced image of 114 different people taken under the visible lightening condition. Collection E: including 942 half faced image of 302 different people and 3d images dependent on 2D images. Collection G: including 783 images of 235 different people and 3d images dependent on 2D images. Collection J2: including 1800 images of 415 different people and 3d images dependent on 2D images.Samples of UND database is shown in figure 2.



Collection E

Collection G

Collection J2

Fig .2 Samples image of UND database

IV.PERSON IDENTIFICATION METHODS USING 2-D IMAGE

A.FEATURE EXTRACTION METHOD PRINCIPLE COMPONENT ANALYSIS (PCA)

Chung, et al (2003) built a multi model recognition system based on face and ear for 2-d ear images. They used manual coordinates of fossa and auricle for person identification. Their person identification is based on the concept of ear, using principal component analysis (PCA). Recognition rate in this method performance is reported %72.7compared to %90.9 for the multimodal system, using 114 subject from the UND, collection F database[1]. Zhang et al (2005) this system is a combination of independent component analysis and based on radical function network. Original ear image in database is decomposed into linear combinations of several basic components. They used two database which segmented ear image to achieve the recognition rate of 94.1%. The first is Carrara University database consists of 102 grey-scale images (6 images for each 17 subjects), second is USTB database 1 consists of 180 images (3 images for each 60 subjects)[2].

Studying PCA for person identification using ear biometric, this algorithm used ear feature vector and the image come from PCA performance on images, for segmentation and recognition. Then the capability of ear image in person identification is verified. However this process is completely automatic since the dependence of algorithm to key point of image which is detected manually.

B.EAR IMAGE CONTOUR EXTRACTING AND FORCE FIELD IMPLEMENTATION

M. Abdel-Mottaleb and J. Zhoudo made the identification process transforming force field based on contours made by these features.Force field method on contours is shown in figure 3.They collected a database including 104 different subjects, one image for each person in training phase. They showed a part for extracting of matching contour. Recognition of the represented ear is a way to use the 58 images of 29 different subjects. Their best level of identification was %87.93recognition rate[3].

In these methods if the head of the input system subjects bend upward or downward (in a way ear image rotates), they cannot identified the person based on his image.

Dong and Mu (2008) used force field transformation and developed a method for recognition of multi posed ear. Force field transformation based on kernel fisher is not sufficient to present a non-linear relation of data. But because of



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

simplex method of Non-Linear Discriminant Analysis (NKLDA), ear image is cropped manually from the original and continue processes like noise filtering and normalization of image. They reported recognition rate of 75.3% for 25°rptation and 72.2% for 30° and 48.15 for 45° from the USTB database IV[4].

These methods is based on energy feature of 2D images. Used force field to find force lines in a way that each image is considered a force source affected by the other points in the image. So features of the force field included the point defined manually on the image before. Distance and angel between the force lines is for calculating the statistic parameters of each image.

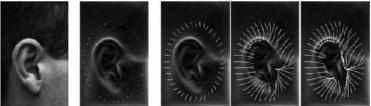


Fig 3:Force field based on contour [3]

C. GENERAL FOURIER DESCRIPTOR (GFD) METHOD

Abate, et al (2006) used rotation invariant descriptors named GFD to extract meaningful features from ear image. These descriptors strong enough against ear rotation and lightening change that reduce recognition rate. They study method themselves presented using database themselves collected. First set included 210 ear image from 70 different subjects, 3 image from each one with the rotation of 0° , 30° , and -30° . Second included 72 images from 36 different person, two images from each person with free rotation taken experiential. In the best rank they get recognition rate of 85% in comparison with the last algorithms that were 50% and 20% for rotation of 15° and 30° [5].

If the purposed distance from camera is different from that s in the database (saved training images in database) system would confront a problem and cannot identify with a high recognition rate.

D.DECOPMPOSED THE IMAGE TO SET OF SUB IMAGES AND USING WAVELET

Nanni and Lumini (2007) used a multi matcher system, that each matcher used feature extracted from a single sub window of 2D image. The ear was segmented using tow marks. The features were extracted by convolution of each sub window with a bank of Gabor filters. Then their dimensionality was reduced using lapels. The best matchers corresponding to the most discriminative sub windows. A sample of sub window and Gabor filter was shown by figure4.To select sub windows with an appropriate matching score run sequential forward floating selection (SFFS) method. Using 114 subjects from the UND database collection E they could achieve a recognition rate of 84% and the best rank recognition rate of 93%. For verification of experiments used the area under the ROC curve and achieving 98.5% recognition rate to present a good performance. However the extended information of extracted features and the need to reduce them, there's still a defect in this method[6].

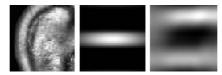


Fig 4:Sub image of ear in Gabor filter[6]

Nosrati, et al (2007) applied a 2D wavelet to normalize ear image. They used template matching for ear extraction. Then they found the independence features in horizontal, vertical and diagonal directions. They used a decomposed image to generate a feature matrix using the weighted sum rule. Finally they applied PCA to reduce feature matrix dimensionally and classification. They achieved a recognition accuracy of 90.5% based on the USTB database[7].

Wang, et al (2008) present a new method using uniform local binary pattern (ULBP) composed by a Haar wavelet transform. Then ULBP were combined simultaneously with block-based and multi resolution methods to describe the texture feature of ear. Sub images transformed by the Haar wavelet prepared an ear field to describing and using the



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

nearest-neighbour method. Using the USTB database 4, they achieved a recognition rate of 100%, 92.4%, 62.6% and 42.4% for angles of 5°, 20°, 35°, and 45° respectively[8].

High extended data in this method force them to use methods reducing dimensional extracted features such as Laplasian matrix method which makes the vector extraction features process slow.

E.LOCAL LINEAR EMBEDDING

Feng and Mu (2009) using local linear embedding (LLE) based on projecting data in high dimensional space in a system, presented single coordinates with lower dimension. Using neighbouring relationships and discovering the data with feigned structure data, showed LLE can do better in solving problem of dimensionality reduction. However it still suffers from lack of labelled information in subcategory of the database. In improved version of LLE called IDLLE first lowered dimensional of the data points using LLE algorithms then adopted linear discriminant analysis (LDA) to solve the problem of person identification classification based on ear image. Using 79 subjects from the USTB database 4 without mentioning how the steps of recognition and normalization performed, they achieved the recognition rate of 60.75% and 43.03% with posed angle of 45° and -45° respectively, with LLE method[9].

F.PRESENT FEATURE DESCRIPTOR OF SIFT AND GABOR FILTER

Kisku, et al (2009) used SIFT features descriptors for structural representation of ear images. By developing an ear skin colure model and using Gaussian mixture model (GMM) and clustering ear coloured pattern, they used vector quantization. They applied K-L divergence to the GMM framework for recording the coloured similarity in the specified ranges and comparing colour similarity between a pair of reference models and probe ear image. After manual segmentation of ear image presents regions of colure slice by extracting SIFT key points. Matching key points on SIFT method is shown in figure 5. They tested a database of 400 subjects with 2 images per subject, and the experimental results showed recognition rate of 96.93% [10].



Fig .5 Matching of key points on SIFT method[10]

Wang and Yuan (2010) extracted local feature frequency using GABOR filter then selected privileged features from general discriminator methods. In this experiment they compared between performances of Gabor filters using USTB database. Different mixture of direction finder and scales in this filters used to have their effects in the first ranking in identification process. The above mentioned database including 308 images from 77 different person. Finally they achieved recognition rate of %99.1 in their best performance[11].

Kumar and wu (2012) presents a new method for ear recognition. This method is based on information phase from GABOR algorithm filters for coding structural place of ear. Information phase coding is saved on grey level of normalized image. Extraction of features is done by Gabor algorithm filters. They used a mixture of different Gabor algorithm filters to compare and concluded between them. The best performance for Gabor algorithm methods is between 96.06% and 95.93% with a database including 753 images of 221 person[12].

G. EXTRACTION OF INDEPENDENT PRINCIPLE COMPONENT A DEVELOPED PCA

Hanmandlu (2013) used LPIC and a developed PCA for recognition rate. PCA is a known method used all of strong pixels, while can't extract all of the detail from ear image. They presented concepts of collection information and penetration force of local information. Features based on local information is presented as LPIC input. LPIC is used not only for local information but also for helping to reduce dimension of features got from PCA method. For extracting broad information from ear used features like information effect, energy feature and complex feature from LPIC to reduce the number of features and applied for inner classification. They used database with controlled and uncontrolled environmental situation to show LPIC effect and classification of IPC. The database used to verify occluded image was S015DB3 which achieved in high level real admission rate of 93.5% (GAR) with 0.1% FAR[13].



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

H.EXTRACTING GEOMETRICAL SHAPE OF EACH EAR IMAGE

Anwar, et al (2015) presented a new ear recognition algorithm based on geometrical features like shape, average, centre and Euclid distance between pixels.in this algorithm pre-processing phase starts with unifying all the images. Then used Mari model for ear recognition of image and used the middle filter to remove noise. Also transformed image into Binary format. They used edge Kenny function and improved image. They extracted features by calculating the longest boundary and distance matrix. Finally classified extracted features using nearest neighbourhood with absolute distance error. They achieved recognition rate of 98% using IITD database. This method is constant against scale and rotation, while it's not an effective method to prevent redundancy of identification rate of database with occluded image, corresponding to feature dependence to boundary and edge[14].

However it seems method based on geometrical parameter achieved a high identification accuracy in personal identification, have challenges: geometrical methods is so sensitive about the outset layer of the ear and first and last point of outset boundary is dependent on the fixed boundary point of the ear to get environmental parameters. So changes in lightening lead to errors of outset ear layer recognition, finally have damages in features. Also changes in ear background such as hair, earring or glasses effect on last point recognition.

V.CHALLENGING PROBLEM OF OCCLUSION EAR IMAGES IN IDENTIFICATION

In the above mentioned papers some problems of ear recognition was different lightening or different position of a person in the time of taking photos. One another problem is occlusion occurred by hair, hat or other obstacles, in a way that the redundancy of 50% in ear recognition is reported in ladies s images.

Arbab-Zavaret al (2007) recognized features of ear images using SIFT. Ear images is taken from the head part of each person images in recognition of a profile. Ear image is selected from features recognized and verified. They compare their profits of their model with PCA and analyse its effects on occlusion[15]. In continue Bustard and Nixon (2008) evaluated the technique using various occlusion ratio and presented the best rank of 92%, 74%, 30%, 20% recognition rate for top ear occlusion. But the other part occlusion like downward and centre is not studied in this work[16].

Bustard and Nixon (2010) proposed a robust method for ear recognition using homographic calculating from the Scale Invariant Features Transform (SIFT). Authors also showed that performance of this method degraded by increasing of occlusion. The feature matcher is achieved by reducing gallery size. Ranking is achieved using a 2D algorithm based on special distances. There is also an analysis on recognition ranking and discriminate of them for rotation of $+13^{\circ}$ and -13° and 18% occlusion. In addition an accurate recognition applied for masked ear images with 20*35 pixels. However the method is not an appropriate one for occlusion detection[17].

Yuan, et al (2010) separated the normalized ear image into 28 sub windows. Then they used neighbourhood for feature extraction on each sub window and selected the best sub window based on recognition rate. Fin

ally they applied weighted to evaluation of ear image that were occluded at top, middle, bottom, left and right respectively[18].

Yuan and chun Mu(2012) presented a 2D ear recognition method based on composition of local information on image of the database with partial occlusion on ear image. Each 2D ear image is separated into sub windows then using prepared neighbourhood to extract features from each sub window. They selected the best sub windows to achieve a high recognition rate. Each sub window is related to a sub class. Sub class method is used for ear recognition with partial occlusion. Ear image was divided into sub windows is shown by figure 6. Experimental result on USTB and UND showed that using sub windows method help us to detect the most meaningful part of ear. Extraction result of this work is with data have occlusion of 33% in two sides or even up to 50% occlusion. Recognition rate rank1 is dependent on 28 sub class extracted from 28 sub window of each image. 78% recognition rate is achieved in rank1 of 24th sub class of USTB database with 50% occlusion, with the same occlusion in UND database in 19th sub class 72% rate is achieved[19].



(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

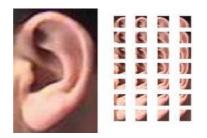


Fig .6Ear image is divided into sub windows[19].

A. SCATTERING DESCRIPTORS OF RESOLVE OCCLUSION PROBLEM

Yuan, et al (2016) presented an occlusion descriptor to code occluded part of the original image. Representation of scattering based on classification is an appropriate action for ear recognition with partial occlusion. A large number of points from occlusion normal descriptors made valuable calculating applying scattering representation of classification (SRC) model. Non negative descriptors included extracted Gabor features descriptors and non-negative occlusion descriptors. Coefficient scattering coding is assumed to be non-negative and with the most scattering condition. Non-negative descriptor showed an increased in discriminative capability. Experimental results on USTB database subset3 with natural occlusion is as following: 100% of recognition rate in a case with no occlusion and recognition rate of 93.8%, 85.4%, 79.2% for 15%, 25%, 35% occlusion respectively[20].the ear dataset with hair occlusion is shown in figure 7.

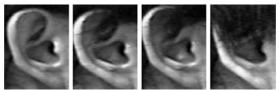


Fig .7Samples images of the ear dataset with hair occlusion.

VI.CONCLUSION

We present an analysis of ear 2D biometric image covering ear recognition and identification system. It presented method of ear recognition and a special attitude toward feature extraction method using Gabor filters and a report of their performance. Ear recognition is still a new field for research. Also most of them didn't study image with damaged factors like differences in position, lightening, and occlusion. But recent studies included these factors in a way that future studies in this field is needed ear recognition system under this condition and using appropriate database that taking photos in real condition. We collected an organized study of important available database, ear recognition and one of the most challenging problem of ear recognition that controlled system confronted.

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(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 8, August 2016

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