Performance Evaluation of PPCA-CPD Human Ear Recognition Application on AMI and USTB Ear Image Datasets

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Abstract:
The paper aims towards development and testing the performance of an image processing based Ear Recognition Application was using combination of Probabilistic Principal Component Analysis (PPCA) and Coherent Point Detection (CPD) techniques in MATLAB. The developed system is used for human identification based on ear lobes; uses high-quality classification methods and accurate feature extraction, which is very significant to execute the system in actual operating environment. The first dataset of images from AMI (Mathematical Analysis of Images) Ear Database consists of 210 ear images from 30 Classes with a number of 07 ear images per class and the second dataset of images from USTB (University of Science & Technology Beijing) Ear Database consists of 200 ear images from 20 classes with a number of 10 ear images per class. The AMI Ear Database consists of color ear images in .jpg/.jpeg file format and USTB Ear Database consists of grayscale ear images in .bmp i.e. Bitmap file format.

Keywords: MATLAB, ear biometrics, AMI Database, USTB Database, PPCA-CPD.

I. INTRODUCTION

The human ear is a perfect source of data for passive person identification in many applications. In a growing need for security in various public places, ear biometrics seems to be a good solution, since ears are visible and their images can be easily taken, even without the examined person’s knowledge. Human ears have been used as major feature in forensic science for many years (for example in airplane crashes). Ear prints, found on the crime scene, have been used as a proof in over few hundred cases in the Europe and the United States. Nowadays, police and forensic specialists use ear prints as a standard proof of identity\cite{1}. There are many advantages of using the ear as a source of data for human identification. Firstly, the ear is one of the most stable human anatomical features. It does not change considerably during human life. Furthermore, the ear is one of our sensors, therefore it is usually visible (not hidden underneath anything) to enable good hearing. Reliability in personal authentication is a key to the stringent security requirements in many application domains ranging from airport surveillance to electronic banking. Many physiological characteristics of humans, \textit{i.e.}, biometrics, are typically invariant over time, easy to acquire, and unique to each individual. The first step of ear recognition is the segmentation of ear image from the profile face. Ear images taken at different time can vary significantly due to changes in hair length and color. Due to this variation many false point matches may occur and this reduce the accuracy of image distance measurement significantly \cite{2}.

The use of 2D or 3D ear images for human recognition differs from the use of earprints: marks left by secretions from the outer ear when someone presses up against a wall, door, or window. Earprints have been introduced as physical evidence in several criminal cases in the US and other countries, although some convictions that relied on earprints have been overturned. Earprints haven’t been widely accepted in court due to a lack of scientific consensus as to their individuality.

Figure 1: Earprint Sample \cite{3}
Currently, there are no commercially available ear recognition systems. However, the future holds tremendous potential for incorporating ear images with face images in a multi-biometric configuration, even as researchers continue to refine the technology. For example, assigning an ear image to one of several predefined categories could allow for rapid retrieval of candidate identities from a large database. In addition, the use of ear thermograms could help mitigate the problem of occlusion due to hair and accessories. As the technology matures, both forensic and biometric domains will benefit from this biometric [3].

![Figure 2: Salient features of external ear (2d and 3d views of same ear) [3]](http://ijesc.org/)

**II. USING THIS TEMPLATE**

H. Dai et. al. present an iterative process of refinement for 3D Morphable Model (3DMM) of the human ear that employs data augmentation. The process employs the following stages 1) landmark-based 3DMM fitting; 2) 3D template deformation to overcome noisy over-fitting; 3) 3D mesh editing, to improve the fit to manual 2D landmarks. These processes are wrapped in an iterative procedure that is able to bootstrap a weak, approximate model into a significantly better model [4]. S. Bharath et.al. use image processing approach and Watershed Segmentation algorithm, to segment an image into regions for better results. For the purpose of result and analysis, experimental MATLAB tool is very useful for result oriented works. Biometrics is analysis of physical or behavioral characteristics that can be used for human identification. There are several typical means of recognition which include access cards, personal identification number (PIN), passwords etc. They can be lost, stolen, duplicated, cracked or shared. These drawbacks can cause a great loss to the concerned. In this paper authors have used ear as a biometric for validation and verification of a user to determine their identity or to verify a claimed identity. Ear is a stable biometric and does not vary with age. This is a standard technique in forensic investigation and has been used as evidence in hundreds of cases. Ear recognition is unique identification technique rather than face recognition, fingerprint recognition so on. The input ear image is pre-processed and segmented, based on the matching percentage attendance is marked for that concerned user and displayed as output [5]. Khiarak et.al. publish that the biometrics of the ears have both advantages and disadvantages compared to other physical attributes. The small surface and the relatively simple structure have a controversial effect. In a positive way, these features provide faster processing compared to face detection and make detection easier compared to fingerprints. On the other side, like other biometrics, current ear biometric recognition systems are vulnerable to attacks. A spoofing attack occurs at sensor level and every imposter can masquerade as someone else by altering data, thus, obtaining an illegitimate access. Due to a lack of anti-spoofing databases, that would support this paper, ear fake databases have been built using different mobile phones. In this paper, an ear presentation attack detection database is collected which contains a various range of variations of potential attacks. In particular, the database consists of two main parts, a) AMI dataset which has 700 ear images and authors make display attack by using them, b) data collected at University of Tabriz containing 20 genuine subjects and fake ears which are made from the genuine ears [6]. Zarachoff et. al. examines the performance of Principal Component Analysis (PCA) based ear recognition in conjunction with super-resolution algorithms from low-resolution ear images. Ear images are first split into database and query images; the latter are first filtered and down-sampled, generating a set ear images of different low resolutions. The resulting low-resolution images are then enlarged to their original sizes using an assortment of neural network-based and statistical-based super-resolution methods. PCA is then applied to the images, generating their eigenvalues, which are used as features for matching. Experimental results on the images of a benchmark dataset show that the statistical-based super-resolution techniques, namely those that are wavelet-based, outperform other algorithms with respect to ear recognition accuracy. Ear recognition is a field in biometrics wherein images of the ears are used to identify individuals. Many techniques have been developed for ear recognition; however, most of the existing techniques have been tested on high-resolution images taken in a laboratory environment [7]. L. Yuan et.al. publish that ear detection is the first step of ear recognition. This paper proposes a real-time ear detection system based on embedded systems. An improved YOLO network is proposed for ear detection. With the same network depth, the width of the improved yolov2-tiny network in YOLO has been reduced to a quarter of the conventional network. By introducing batch processing and reducing the regularization coefficient of the improved yolov2-tiny network, the detection accuracy has been improved and the detection time has been reduced. The proposed model is more applicable for embedded implementation. On Nvidia Jetson tx2 real-time detection of the ear has been realized. The image is captured by an external camera and the ear will be marked when the ear appears in the image. On Nvidia Jetson tx2, the real-time detection frame rate is 30 frames per second which can meet the real-application requirements [8]. Yaman et.al. present a detailed analysis on extracting soft biometric traits, age and gender, from ear images. Although there have been a few previous work on gender classification using ear images, to the best of our knowledge, this study is the first work on age classification from ear images. In the study, authors have utilized both geometric features and appearance based features for ear representation. The utilized geometric features are based on eight anthropometric landmarks and consist of 14 distance measurements and two area calculations. The appearance-based methods employ deep convolutional neural networks for representation and classification. The well-known convolutional neural network models, namely, AlexNet, VGG-16, GoogLeNet, and SqueezeNet have been adopted for the study. They have been fine-tuned on a large-scale ear dataset that has been built from the profile and close-to-profile face images in the Multi-PIE face dataset. This way, authors have performed a domain adaptation. The updated models have been fine-tuned once more time on the small-scale target ear dataset, which contains only around 270 ear
images for training. According to the experimental results, appearance-based methods have been found to be superior to the methods based on geometric features. Authors have achieved good accuracy for gender classification, whereas low accuracy has been obtained for age classification. These results indicate that ear images provide useful cues for age and gender classification, however, further work is required for age estimation [9]. Moghaddam et.al. address for the first time the ear presentation attack detection problem by developing an exhaustive benchmarking study on the performance of state-of-the-art light field and non-light field based ear presentation attack detection solutions. In this context, authors also propose an appropriate ear artifact database captured with a Lytro ILLUM lenslet light field camera, including both 2D and light field contents, using several types of presentation attack instruments, including laptop, tablet and two different mobile phones. Results show very promising performance for two recent light field based presentation attack detection solutions originally proposed for face presentation attack detection. Ear recognition has received broad attention from the biometric community and its emerging usage in multiple applications is raising new security concerns, with robustness against presentation attacks being a very active field of research [10]. Sarangi et.al. examine the feature-level fusion of two contactless biometric modalities of the same image i.e. ear and profile face. Initially, two most efficient local feature descriptors such as LDP (Local Directional Patterns) and LPQ (Local Phase Quantization) are used to represent both biometric modalities. Due to combination of two feature descriptors, dimension of the feature sets are increased and so PCA is separately applied to both modalities before normalization and fusion steps. Finally, to obtain more Discriminant nonlinear features the Kernel Discriminative Common Vector (KDCV) method is employed after fusion to the combined feature vector. Experimental evaluation on University of Notre Dame (Collection E) side face database clearly reveals the proposed method is more efficient to increase the recognition performance over other existing ear based unimodal and multimodal biometric systems [11].

III. METHODOLOGY

In a verification system, the user shows his/her identity when trying to access within the system and presents his/her biometric trait to the system. Then, a sample is given as input from Ear database and processed in order to extract the biometric features, which are compared against the user’s template previously stored in the system. In that way, the system makes a one-to-one comparison between the sample and the pattern, resulting in a numerical value which indicates their degree of similarity. The decision module evaluates the result of this comparison and accepts or rejects the user identity depending on a threshold previously set on the system. The statistical method Proabilistic Principal Component Analysis (PPCA) has been selected as a feature extractor, and the matching of features is performed by a distance-based classifier including Euclidean and Eigen distances. The system has been designed following the typical structure of biometric verification systems and is composed of the following modules: images acquisition from database, images preprocessing, features extraction, database of biometric templates and comparison. In this proposed work an ear geometry-based biometric verification system using PPCA Probabilistic (CPD) The figure below shows the proposed system. Global correspondence optimization solves simultaneously for both the deformation parameters as well as the correspondence positions. It is to consider the alignment of two point sets as probability density estimation and the method is called Coherent Point Drift (CPD). The CPD approach is extended to apply in a hierarchical parts-based CPD-PCA morphing framework to avoid under-fitting and over-fitting of the ear shape and features.

Figure.3.Proposed System Block Diagram Ppca Human Ear Recognition

Pre-processing:
A good preprocessing of the images is crucial to improve the system performance. To this end, it is necessary to remove those areas which do not contain information about the ear as well as to improve their quality and adapt them for the feature extraction step.

Feature Extraction:
In basic system the feature extracted using basic principal components which is modified using probabilistic principal component analysis. Principal Component Analysis (PCA) has been selected to extract the ear features from the image. Accordingly, the ear-space that provides the best representation of the ears belonging to the different individuals has been searched. This space is composed of vectors named principal components, which correspond to the most descriptive ear features, are uncorrelated and maximize the variance that the images present. Principal Component Analysis is a powerful and most popular feature extraction technique. PCA is used for reducing dimensionality by avoiding redundant information without much loss. This is one of the most used feature extraction techniques for pattern recognition and compression. PCA uses linear transformations for mapping data from high dimensional space to low dimensional space. In PCA, features of the image are stored in the form of eigenvalues and eigenvectors. The Coherent Point Drift (CPD) algorithm is applied with a non-rigid deformation model (shape of the ear), followed by a projection to corresponding points that is regularized by the template shape-preserving PCA operator. Such a deformation regulation process was applied by motivation for the deformation process is that the deformed template is able to preserve the same shape, the same number of vertices and also the same triangulation relationship as the over-fitted data, while it can overcome the noise due to over-fitting. The deformation algorithm works well because there is a known one-to-one correspondence (1:1 Match). The proposed modification i.e. PPCA is technique in which features with high probability of occurring and importance for ear recognition are included in calculating the matching biometric comparator. This is done by application of probabilistic
algorithm approach called Coherent Point Drift (CPD) applied to PCA features i.e. Eigen ears.

**Distance Based Matching (Euclidean Distance):** Distance-based matching has been selected to compare feature vectors due to it is one of the most extended methods in biometrics given its simplicity and low computational requirements. It provides a numeric value as a result, which represents the data dissimilarity. Accordingly, the decision policy established in the system is to consider the compared vectors as belonging to the same person if the computed distance is lower than a previously established threshold. The distance used as biometric comparator is Euclidean distance. The last step in the ear recognition is to classify whether query ear image is in our database or not. In this application Minimum distance classifier is used. Here, Euclidean distance of ear image is calculated after projecting Eigen ear on ear space. After calculating Euclidean distance, a class who has nearest Euclidean distance is selected. The last step in the ear recognition is to classify whether query ear image is in our database or not. This system has used a Minimum distance classifier. Here, Euclidean distance of ear image is calculated after projecting Eigen ear on ear space. After calculating Euclidean distance, a class who has nearest Euclidean distance is selected.

**IV. RESULT ANALYSIS**

The results are obtained for PPCA-CPD Human Ear Recognition System by development of a robust user-interface in MATLAB programmatically as well as using GUIDE. The application GUI’s for PPCA-CPD Human Ear Recognition System using Probabilistic Principal Component Analysis and Coherent Point Detection Algorithm is developed and tested using database entry samples from two datasets from two different Ear Image Databases. The two databases are namely AMI Ear Database and USTB Ear Database. The first dataset of images from AMI Ear Database consists of 210 ear images from 30 Classes with a number of 07 ear images per class and the second dataset of images from USTB Ear Database consists of 200 ear images from 20 classes with a number of 10 ear images per class. The AMI Ear Database consists of color ear images in .jpg/.jpeg file format and USTB Ear Database consists of grayscale ear images in .bmp i.e. Bitmap file format. The application tested on a total of 410 images combined from the two databases and results are recorded and compared for performance analysis of PPCA technique for one-to-many (1: N) matching criteria and CPD technique for one-to-one (1:1) matching criteria. The performance analysis is based on the parameters like Euclidean Distance, Ear Space Distance, and Matching Output Class number.

**Table.1.Ear Image Datasets for Result Analysis and Performance Evaluation**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>File Format</th>
<th>No. of Classes</th>
<th>Images per Class</th>
<th>Total Images per Dataset</th>
<th>Total Ear Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset 1</td>
<td>jpg (Color)</td>
<td>30</td>
<td>07</td>
<td>210</td>
<td>410</td>
</tr>
<tr>
<td>Dataset 2</td>
<td>bmp (Grayscale)</td>
<td>20</td>
<td>10</td>
<td>200</td>
<td></td>
</tr>
</tbody>
</table>

The MATLAB Command window showing ear recognition results with Nearest Class, Euclidean Distance, Distance from ear space values.
V. CONCLUSION

Ear detection is extremely important for various applications in Computer Vision and Bio- metric systems. In the biometrics community, ear detection is an extremely important step in an ear recognition system. It has also been used to improve the accuracy of face detectors. In this thesis, the proposed PPCA-CPD algorithm is implemented and evaluated for performance on two databases AMI Ear Database and USTB Ear Database. The first dataset of images from AMI Ear Database consists of 210 ear images from 30 Classes with a number of 07 ear images per class and the second dataset of images from USTB Ear Database consists of 200 ear images from 20 classes with a number of 10 ear images per class. The AMI Ear Database consists of color ear images in .jpg/.jpeg file format and USTB Ear Database consists of grayscale ear images in .bmp i.e. Bitmap file format. For the AMI Ear Database as it contains color images the value is high and should be less than 15000 and for USTB Ear Database which consists of Grayscale images the value falls close to zero. The ED Values are calculated and recorded for 210 images of AMI Ear Database.
and 200 images of USTB Ear Database. For AMI Ear Database ranges between 5000 and 15000 for correct match and has greater than 15000 for incorrect match. For USTB Ear Database this value falls close to 0 and incorrect matches are due to the incompatibility of application to the 02 database images. For the AMI Ear Database as it contains color images the value is high and should be less than 8000 and for USTB Ear Database which consists of Grayscale images the values fall in low ranges. The ESD Values are calculated and recorded for 210 images of AMI Ear Database and 200 images of USTB Ear Database. For AMI Ear Database ranges between 3000 and 8000 and for USTB Ear Database this value falls close to 0 to 10. The AMI Ear Database Dataset1 has 185 correct image class matches out of 210 leading to a high % accuracy performance of 88.09% and 25 incorrect image class matches leading to lowest %error performance of 11.9%. The USTB Ear Database has 198 correct image class matches out of 200 leading to a even higher % accuracy performance of 99% and only 02 incorrect image class matches leading to lowest %error performance of 0.01%. The PPCA-CPD ear recognition application shows considerably better performance when tested on USTB Ear Database Dataset2 than AMI Ear Database Dataset1 with %accuracy deficit rate of 10.91%.

VI. REFERENCES


