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Short Communication

Ear Recognition for Automated Human Identification

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Abstract

This paper investigates a new approach for the automated human identification using ear imaging. We present a completely automated approach for the robust. Segmentation of curved region of interest using morphological operator sand Fourier descriptors. We also investigate new feature extraction approach for ear identification using localized orientation information and also examine local gray- level phase information using complex Gabor filters. Our investigation develops a computationally attractive an defective alternative to characterize the automatically. Segmented ear images using a pair of log Gabor filters. The experimental results achieve average rank-one recognition accuracy of 96.27% and 95.93%, respectively, on the publicly available database of 125 and 221 subjects. Our experimental results from the authentication experiments and false positive identification verses false negative identification also suggest the superiority of the proposed approach over the other popular feature extraction approach considered in this work.

Keywords: Ear recognition, automated human identification.

Introduction

Reliability in personal authentication is the key issue for the stringent security requirements in many application domains ranging from airport surveillance to electronic banking. Many physiological characteristics of humans, i.e., biometrics, are typically in variant over time, easy to acquire , and unique to each individual. Therefore the biometrics traits are increasingly adopted for civilian application sand no longer confined for forensic identification. Most of the current research in biometrics is focused on face, finger print, gait, signature, iris, palmprint, or hand-geometry. However, there have been little efforts to investigate the human ear for personal authentication despite its significant role in forensic science. The ear is quite attractive biometric candidate mainly due to its i. rich and stable structure that is preserved since birth and is quite unique in individuals, ii. being invariable to the changes in pose and facial expression, and iii. relatively immune from anxiety, privacy,and hygiene problems with several other biometric candidates. Therefore automated personal identification using ear images has been increas- ingly studied for possible commercial applications.

Related Work: Human ear has attracted several studies on its individuality and uniqueness. Iannarelli[1] has manually measured the distance between predicted points on human ear. He has extensively examined 10,000 ear sand concluded on their uniqueness. The utility of Iannarelli's approach for the automated ear recognition is quite limited since this approach required accurate estimation of as table reference points for measurements, which is very difficult in real environment. The ear image characterization using Voronoi diagram is illustrated in[2,3]. However, the work is largely conceptual and lacks experimental results on any ear database. Hurley et al.[4,5] ave presented one of the most promising approaches for the automated ear identification and developed a new method of localizing ears have features using force field transformation. Authors have employed the database of 63 users to illustrate the appearance-based ear recognition. Chang et al.[6] investigated principal component analysis to characterize ear and face using eigen ear and eigen face, respectively. The rigorous experimental results detailed in achieve competing performance from these two independent modalities and illustrate that the combination of these two modalities can achieve convincing improvement in the performance for the human identification. Shape of human ear is known to be quite complex and has also been characterized using geometrical parameters for the biometric identification. Mu et.al.[7] have attempted such characterization of ear shapes from the gradient of ear images, using long axis based shape and structural feature extraction, and achieved promised results on the database of 77 subjects. More no et al. have detailed the usage of neural network classifiers on ear profile images derived from the gray level ear images. Ear shape features have shown to offer promising performance but on small size databases. Nanni and Lumini have recently exploited the color information from the ear images and detailed the selection of color spaces, using the sequential forward floating selection, when the fitness function is related to the optimization of performance from the ear recognition. Human ear is highly curved 3D surface and therefore provides rich 3D discriminent features for the biometric identification. Bhanu and Chan[8] have exploited the local surface shape descriptors for the 3D ear identification. These authors have also suggested iterative closest point matching (ICP) for the matching of 3D ear shapes. One of the most promising approaches for the automated ear identification using 3D imaging is presented by Yan and Bowyer[6]. This approach is based on the active contour function to localize ear shape and uses ICP that uses k–d tree data structure to efficiently search for closest point. The use of ICP for characterization of 3D ear shape has also been detailed[1]. The slow acquisition speed of 3D ear imaging (such as Vivid 910 3D digitizer employed in the literature), limits the online usage of 3D imaging for the civilian applications. The currently employed 3D digitizer in the literature is also quite expensive and large in size. Therefore our focus in this work has been to exploit the 2D ear images that can be conveniently acquired from conventional digital camera.

Automated Ear Identification

One of the most challenging aspects of the 2D automated ear identification is related to the automated and accurate segmentation of ear or the region of interest that encloses discriminant gray level information. The human ear is highly curved 3D surface and therefore generates in uneven reflections which also generate shadows. Therefore the acquired images have uneven illumination, low contrast, and often surrounded by hairs and skin with varying pigmentation. Therefore the most challenging aspects of developing automated ear identification, as observed from our study, is to develop a robust algorithm that can reliably segment a fixed region of interest for the extraction of features that are more stable in a given class/subject.

Each of the acquired images is firstly subjected to the pre-processing that consists of smoothing with a Gaussian filter which helps to suppress noise, followed by histogram equalization. The resulting image is used to automatically generate abinarized mask that can outline the surrounding region of interest. This step requires the binarization of image using Otsu's threshold. The resulting image however generates them ask so varying sizes (primary due to uneven and varying illumination) and therefore this thresholding limit is automatically adjusted until the mask area is less than the predefined limit. The pre-processed image is also simultaneously used to ascertain the shape mask that reliably captures the ear shape. This is quite challenging due to the presence of shadows, surrounding skin, hair and our efforts to localize the ear shape using spatial and spatial-domain filtering yielded poor results (extracted regions were not stable). We therefore pursued with a series of gray scale morphological operations to extract the ear shape. The morphological operations typically compare the ear image with another known object, i.e., structuring element. The shape and size of such structuring element is determined during the training phase from the prior knowledge of acquired ear images with the objective of effective ear localization (with in a given region) and noise elimination. The shape of structuring element is primarily selected to probe the presence of wide line-likes have corresponding to the width which is determined by the size of structuring element.

Feature Extraction and Matching

The accuracy of automated ear identification approach is highly influenced by the nature of extracted features and the employed matching process. In this work, we investigated three new feature extraction and matching approaches for the identification of automatically segmented ear images. The extraction of phase information using 1D log-Gabor and 2D Gabor filters was firstly investigated for the ear identification. The spatial orientation of gray level shape features can be efficiently encoded using even Gabor filters and such orientation details can be employed to generate templates for the matching. Therefore such feature extraction approach using a bank of even Gabor filter was also investigated and achieved promising results as detailed. The complex Gabor filters can also be employed to extract local phase information, as commonly used in the iris recognition, and was also investigated in this work. In the following section we briefly describe the feature extraction and corresponding matching approaches investigated in this work.

Conclusion

The experimental results in this paper are presented on publicly available dataset of 465 ear images from the 125 subjects. The left ear images from 125 subjects/volunteers were acquire during simple imaging set up that employed a digital camera in an indoor environment. The images were acquired over a period of 9 months in indoor environment and no additional illumination was employed. Each of the volunteers satona chair and a digital camera was fixed to acquire the region of interest which ensured the presence of earing imaging window. All the subjects in the database are in the age group 14–58 years and provided at least 3 images. Some images from this dataset are reproduced and the images in this dataset have significant scale, translational and rotational variations. A Gaussian filter with m¼20 and s¼5 was employed in the preprocessing stage. The predefined limits for the binarization, i.e., area At is fixed at 25,000 and 0.95, respectively, for all the experiments in this paper. A squared structuring element of size two pixels was selected for the closing operation. The resulting images were subjected to area opening, i.e., removal of isolated and connected pixels if their count is less than 80 while considering their connectivity in 8-directions (boxshape). Each of the acquired images are automatically segmented and normalized, using the approach detailed, to 50_180 pixel size region of interest images. In addition to this database, we also formed a larger dataset that included all the images from the database and this larger dataset is also made available. Therefore a larger version of dataset had 753 images from 221 subjects and is also employed for the performance evaluation. The automated extraction of the field lines from the ear images using force field transform approach, which was also implemented by us for the performance comparison on the sample.

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