Ear Recognition using a novel Feature Extraction Approach

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Abstract

Most of traditional ear recognition methods that based on local features always need accurate images alignment, which may severely affect the performance. In this paper, we investigate a novel approach for ear recognition based on Polar Sine Transform (PST); PST is free of images alignment. First, we divide the ear images into overlapping blocks. After that, we compute PST coefficients that are employed to extract invariant features for each block. Second, we accumulate these features for only one feature vector to represent ear image. Third, we use Support Vector Machine (SVM) for ear recognition. To validate the proposed approach, experiments are performed on USTB database and results show that our approach is superior to previous works.

Keywords: *Ear recognition; Feature extraction; PST; SVM.*

1. Introduction

Reliable user authentication has become an indispensable part in many applications such as access control systems, forensic and commercial applications [1]. Biometric traits are regarded as one of the efficient methods to perform human authentication. It refers to choose a trait based on physiological (face, ear, iris etc) and/or behavioral (keystroke, voice, gait etc) characteristics of an individual. Therefore, biometric systems based on biometric traits are inherently more reliable than traditional systems (password or ID card) which are difficult to remember if the password is too strong and can be stolen if the password is too smaller.

Recently, biometric models have taken very interesting in many applications especially in the field of security; most of researches have presented face [2], iris, hand gesture [3], and fingerprint as a good biometric trait. Ear also is regarded as one of the efficient biometric traits, since human ear has many properties for a potential biometrics like uniqueness, collectible, permanence and universality [4]. Ear is a large, passive trait, which does not change through age [5], or suffer from changes such as facial expression, glasses and make-up. Thus, the ear is increasingly taken attention of researchers to identify people. A variety of ear recognition approaches have been proposed in the literature to extract discriminant features. Abaza et al. [6] provided a detailed survey on ear biometrics; he presented most 2D and 3D approaches proposed for ear detection and recognition both in. These methods are generally designed to extract any of the following three types of ear features: global, geometric, or local appearance features.

For global features, EigenEar, Independent Component Analysis (ICA), ULFDA, 1D or 2D Gabor filters and Haar wavelet [7-9] have been used to extract intensity, directional and spatial-temporal information from human ears, respectively. The HMAX model used to extract features from ear images, and applied support vector machine for final classification have been proposed in [10]. In [11], Zhang and Mu applied a two-step compound classifier system for ear recognition. First, ears were roughly classified by geometric features based on height width ratio. Second, they applied PCA and ICA features for final classification. Also, Zhang et al. [12], they combined ICA and RBF network by decomposing the original ear image database into linear combinations of several basic images and used the corresponding coefficients of these combinations for RBF network. Due to the fast speed and robustness to lighting conditions, many methods have also been proposed to extract geometric features. Rahman et al. [13] described the outer helix with least square curve fitting and applied horizontal reference lines of ear height line to detect the angles as features. Choras et al. [14] extracted contours of ear by referring to geometrical properties such as width, height,

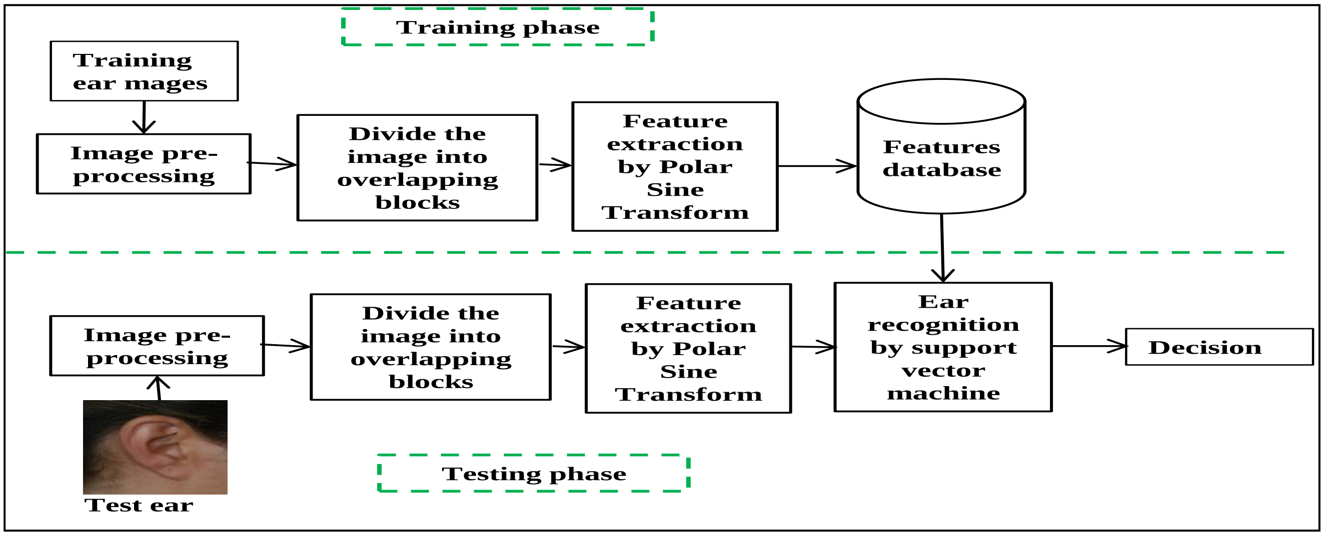

Fig. 1. Diagram of the proposed approach

and earlobe topology, and then proposed four features for ears. Compared with global and geometric features, local appearance features have several unique advantages: (i) robust to the noise, (ii) rich texture information in ear images, and (iii) free of accurate landmark detection. Benzaoui et al. [15] proposed several variants of LBP for automatic ear recognition. Hurley et al. [16] proposed a new approach to perform ear recognition based on force field features. They treated an image as an array of mutually attracting particles that act as the source of a Gaussian force field and use several potential channels and wells to represent human ears. However, most of current methods need accurate image registration and normalization; poor alignment may severely affect the following feature extraction process.

To address these issues, we present a novel approach free of sophisticated image alignment. Specifically, we rely on Polar Sine Transform (PST) [17] to extract rotation invariant local features from ear images. PST has been applied in a number of domains such as face recognition [16], fingerprint classification [18] and achieved great success. Furthermore, we use Support Vector Machine (SVM) [19] to identify the human ear.

The rest of this paper is organized as follows: Section 2 introduces the proposed ear recognition approach. Section 3 presents the experimental results and compares our approach with previous works. Finally, Section 4 concludes the paper.

2. Proposed Approach

In this section, we present the proposed approach for human recognition from ear images. As shown in Fig. 1, our approach involves image preprocessing, feature extraction based on PST, and classification the human ears by SVM. In the following subsections, we will describe each part of the proposed approach.

2.1 Preprocessing

To remove variation in brightness and contrast due to different lighting conditions and camera properties; the ear *f*(*x*, *y*) image need to normalize process, normalization involved offset of the intensity values and adjusting the scale [20] by using Eq. 1.

$$Y(x,y)=\left(f(x,y)-M\right)/S \text{, where} \tag{1}$$

$$M = mean\left(f(x,y)\right), \tag{2}$$

$$S = \sqrt{\sum_{y=1}^{c}\sum_{x=1}^{r}\left(f(x,y)\right)^2 - M^2} \,/(r*c) \tag{3}$$

where $Y(x, y)$ is the normalized output image and c, r are the height and width of the ear image $f(x, y)$, respectively. Figure 2 shows an image from the USTB database and the corresponding normalized image result.

(a) (b)

Fig. 2. Normalized ear image. (a) An ear image from the USTB database, and (b) the corresponding normalized ear result.

2.2 Polar Sine Transform (PST)

PST [17] is a two-dimensional transform based on orthogonal projection bases to generate a number of rotation invariant features. Besides, PST is well suited for applications where maximal discriminant features are needed because it makes available a large set of features for feature selection in order to search the discriminative information. Hence, we choose PST for feature extraction in this paper. Given an ear image *f* (*x*, *y*), its polar coordinate *f* (*r*, *θ*) is defined as:

$$r = \sqrt{x^2 + y^2} \quad , \theta = \arctan(y/x) \tag{4}$$

In [17], Yap PT et al. defined the PST of order *n* and repetition *l* for an image *f* (*r*, *θ*) in the polar coordinates as:

$$M_{nl} = \Omega_n \int_0^{2\pi} \int_0^{1} \left[\sin\left(\pi n r^2\right) e^{il\theta} \right]^* f(r,\theta) r dr d\theta , \quad 0 \leq n,|l| < \infty \tag{5}$$

where $[\,.\,]^*$ is the conjugate operation and

$$\Omega_n = \begin{cases} 1/\pi & ,n = 0 \\ 2/\pi & ,n \neq 0 \end{cases} \tag{6}$$

Also, Yap PT et al. defined the kernel function of PST that consists of a circular component and a radial component as follows:

$$H_{nl}(r,\theta) = R_n(r)\, e^{il\theta} \;=\; \sin\left(\pi n r^2\right) e^{il\theta} \tag{7}$$

where $R_n(r) = \sin\left(\pi n r^2\right)$ is the radial component. For continuous domain, PST can be computed with Eq. (5). However, for a digital image *f* (*x*, *y*) defined on the discrete domain, it is given as follows:

$$M_{nl} = \frac{4\,\Omega_n}{M \times N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} \left[H_{nl}(x,y) \right]^* f(x,y) \tag{8}$$

where $M \times N$ is the size of the digital image.

2.3 Feature Extraction based on PST

After image preprocessing operation; normalize of the ear image. We divided the ear images into overlapping circular blocks with step size 2 pixels. To balance the matching speed and better description ability, we choose the size of blocks as 16×16. We compute the PST coefficients with different values of *n* and l for representing image blocks, satisfying the following equation:

$$Feats_{\ f(x,y)} = \left\{ \left| M_{nl} \right| s.t : n + l \leq 5,\, 0 \leq l \leq 3 \ and \ \ 0 < n \leq 5 \right\} \tag{9}$$

where M_{nl} can calculate from Eq. (8) for digital image *f* (*x*, *y*).

2.4 Ear Recognition

In this subsection, we illustrate how the proposed approach recognizes the human ear. Our approach computes the PST coefficients for each block in ear image. After that, we accumulate these features to only one feature vector represents the ear image. Recently, SVM has been widely used in many different tasks such as object recognition systems and pattern classification. We use SVM for ear recognition. Moreover, we use multi-class problem with SVM for recognition process not a basic SVM that is two-class problem.

3. Experimental Results

The proposed approach is evaluated on the USTB database; subset I [21]. USTB database includes 180 images in BMP format for 60 subjects. Each subject has three images; including a normal frontal image, a frontal image with trivial rotation and an image with different illumination. Figure 3 shows some examples of USTB database.

Fig. 3. Examples of USTB ear images.

For the recognition experiment, we divide the database into two datasets: the first dataset includes two images per each subject (e.g., the first and the second images) for training and the second dataset involves the third image for testing. Table 1 shows the results between the class number and recognition rate for each experiment, which class number refers to the number of subjects that are used for testing.

Table 1: Recognition rate using PST and SVM with different class number of subjects

Class number	10	20	30	40	50	60
Recognition rate %	100	100	96.67	97.50	98	96.6 7

We also compare the proposed method with other works, i.e., PCA, ICA and HMAX with SVM. The experimental results are shown in Table 2.

Table 2: Performance comparison in recognition rate

Approach	***Recognition rate %***
HMAX + SVM [7]	75
PCA + [8]	85
PCA+RBF network [9]	85
ICA+RBF network [9]	88.33
ICA + [8]	91.67
Our approach	**96.67**

Table 2 shows that our approach that depends on PST to extract invariant features from the human ear and use SVM for classification is more effective than HMAX model with SVM [7]. Moreover, our approach is superior to PCA and ICA with roughly and RBF network classification [8, 9].

4. Conclusions

In this paper, we investigate a novel feature extraction approach for recognizing human ears. Different from traditional local feature extraction methods which needs accurate image alignment and normalization; we extract discriminative features for overlapped image blocks by polar sine transform. Also, we use support vector machine to identify the human ear. Experimental results on USTB database show that the proposed approach achieves a better performance compared with others approaches. However, our method may fail when the ear images have poor qualities or is with shadows and hair occlusions. In the further work, more studies will be given to address these limitations.

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