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Identity Recognition from Ear Images Using Local Binary Pattern and Local Phase Quantization

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ABSTRACT

One of the challenges posed by technological advancements in modern society is the issue of identity verification and authentication. Among various biometric identification methods, ear biometrics is a relatively new approach. Identity recognition has garnered significant attention in the realm of biometrics, particularly with the advancement of image processing techniques. Among various biometric traits, ear recognition is emerging as a reliable method due to the unique structure of human ears. The human ear possesses unique characteristics that make it suitable for identity recognition. In this study, we employ Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) operators for pattern recognition in ear images. To reduce the feature vector size and enhance classifier accuracy, we apply Principal Component Analysis (PCA) to the features extracted using LBP. Finally, we utilize the k-Nearest Neighbors (k-NN) algorithm with the Canberra similarity measure for classification. To evaluate the efficiency of our proposed method, we conducted experiments on the USTB-1 database, which contains 180 images from 60 individuals, achieving an accuracy of 98.33%.

1. INTRODUCTION

The issue of identity verification and authentication is one of the major concerns in today’s world. Various methods exist for identity recognition, among which biometric systems are considered highly reliable, producing secure outputs while eliminating risks such as theft, loss, forgetting, or damage. Biometric traits used for authentication must possess four essential characteristics: (1) they must be present in all individuals, (2) they must be unique to each individual, (3) they must remain unchanged over time, and (4) they must be collectable [1].

One of the most intriguing anatomical features for biometric systems is the human ear. The significance and potential of ear biometrics for identification and authentication were first introduced and supported in 1890 by the renowned French criminologist Alphonse Bertillon. The human ear contains a vast amount of distinctive information, which remains unique even among identical twins [2]. Some advantages of using the ear for identity recognition include the ease of image acquisition, as ear images can be captured from a considerable distance without

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requiring the cooperation of the subject [3]. Furthermore, the external structure of the ear remains almost unchanged between the ages of 8 and 70, with any changes being predominantly in scale rather than structure. This stability in ear shape over time is a key advantage over other biometric traits [4].

Additionally, the human ear exhibits a uniform color distribution, ensuring that nearly all essential information is preserved when converting a color image to grayscale. A significant advantage of ear biometrics over facial recognition is its predictable and simple background, as ears are symmetrically positioned on both sides of the head. Moreover, unlike facial expressions, the shape of the ear remains unaffected by emotions such as happiness, sadness, or surprise, and it does not change due to makeup or hairstyle alterations. These factors underscore the efficacy of ear biometrics compared to other biometric traits [5].

In 2005, Zhang et al. introduced a hybrid method for ear image recognition, employing independent component analysis (ICA) and neural networks, achieving an accuracy of 94.11% [6]. In 2007, Ansari et al. used an edge detector to identify the ear region. They categorized edges into convex and concave types, selecting convex edges as candidates for representing the outer ear contour. The connected curved segments that enclosed the largest area were chosen to define the external ear contour. Their method achieved recognition rates of 93.34% and 98.05% on the IITK and USTB II databases, respectively [7].

In 2008, Zhang et al. utilized principal component analysis (PCA) and independent component analysis (ICA) separately for feature extraction, with a radial basis function network (RBFN) for classification. Their results showed that ICA outperformed PCA in feature extraction [8]. In 2010, Alaj et al. used PCA for feature extraction and artificial neural networks for classification, achieving a recognition accuracy of 96.1% [9]. In 2011, Yazdanpanah et al. employed Gabor filters for feature extraction from ear images, attaining an accuracy of 93.33% on the USTB database [10].

In 2012, Kumar applied logarithmic Gabor filters for feature extraction from ear images, reporting a recognition rate of 95.9% on the IITD II database [11]. In 2015, Annapoorani et al. proposed a combined approach, using the overall ear shape as a global pattern and the tragus as a local pattern. These features were extracted separately and then fused. Their findings indicated that the fusion approach, when using the Hamming distance metric, resulted in superior accuracy compared to using either the ear shape or tragus alone [12].

In 2016, Gholami et al. employed the artificial bee colony algorithm to enhance image contrast and used the Scale-Invariant Feature Transform (SIFT) algorithm for feature extraction. Their method achieved an accuracy of 97.15% on the USTB database [13].

The structure of this paper is as follows: Section 2 presents the proposed methodology. Section 3 discusses the experimental results and compares the outcomes of the proposed method. Finally, Section 4 provides a summary of the findings and conclusions of the study.

2. PROPOSED METHOD

In this study, we present a novel approach for ear image recognition that achieves high identification accuracy. After initial preprocessing steps, we extract essential features from images using Local Binary Pattern (LBP) and Local Phase Quantization (LPQ). Subsequently, we apply Principal Component Analysis (PCA) to reduce the dimensionality of the input data. Finally, classification is performed using the k-Nearest Neighbors (k-NN) classifier with the Canberra similarity metric.

Figure 1 illustrates the block diagram of our proposed method for identity recognition using ear biometrics.

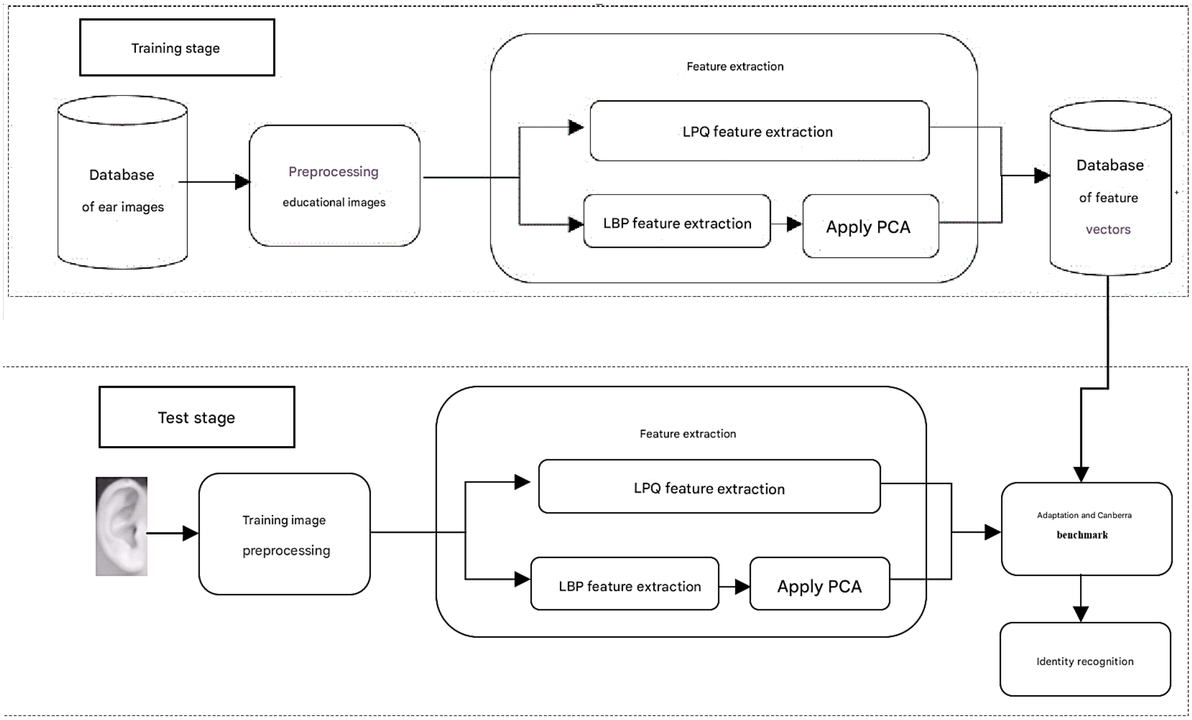

Fig. 1. Block diagram of the proposed method for ear biometrics.

2.1. Image Preprocessing

Before feature extraction, initial preprocessing operations are applied to the ear image to prepare it for further processing. The image is converted to a double format. Since LPQ does not require color information and only utilizes texture details, the images are converted to grayscale during the preprocessing stage. Additionally, all images are resized to 84×108 pixels.

2.2. Feature Extraction

After preprocessing, the image is sent to the feature extraction algorithm. We utilize Local Phase Quantization (LPQ) and Local Binary Pattern (LBP) operators for feature extraction. A total of 512 features are obtained from these two operators for each ear image.

2.2.1. Feature Extraction Using LPQ Operator

The Local Phase Quantization (LPQ) method has gained significant attention in recent years due to its strong performance in texture analysis [14]. The LPQ operator is blur-insensitive and extracts statistical phase features based on quantized phases of the Discrete Fourier Transform (DFT). These features are computed locally within windows of varying sizes for each pixel, ultimately forming a histogram representation.

The LPQ operator derives local phase features using a 2D Discrete Fourier Transform (DFT) or, more precisely, through a Short-Time Fourier Transform (STFT). This computation is performed over an M × M rectangular neighborhood centered at each pixel location x in the image f(x) and is defined as follows:

$$F(u,x) = \sum_{y \in \mathrm{N}_x} f(x-y)e^{-j2\pi u^T y} = w_u^T f_x \quad (1)$$

where w_u represents the basis vector of the 2D Fourier transform at frequency u, and f_x is another vector containing all M^2 pixels from the neighborhood N_x.

A practical approach for computing this transformation is by applying 2D convolution using the function:

$f(x) \times e^{-j2\pi u^T x}$ for all **u**. In LPQ, only four complex coefficients are considered, corresponding to the following 2D frequency vectors: $u_1 = [a, 0]^T$, $u_1 = [0, a]^T$, $u_1 = [a, a]^T$, $u_1 = [a, -a]^T$, where a is a scalar frequency lower than the first zero crossing of H(u).

Here, H(u) represents the Point Spread Function (PSF) in the Fourier domain, which models image blurring. We assume:

$$F_x^c = [F(u_1, x), F(u_2, x), F(u_3, x), F(u_4, x),] \tag{2}$$

and

$$F_x = [Re\{F_x^c\}, Im\{F_x^c\}\ ]^T \tag{3}$$

where *Re* and *Im* denote the real and imaginary components of the complex number, respectively. The corresponding 8 × M² transformation matrix is computed as follows:

$$\mathrm{W} = \left[Re\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_3}\ \}, Im\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_3}\}\right]^T \tag{4}$$

So:

$$F_x = W\ f_x \tag{5}$$

We assume that the image function f_x is the result of a first-order Markov process, where the correlation coefficient between adjacent pixel values is ρ and the variance of each sample is δ^2. Without loss of generality, we assume that $\delta^2 = 1$. Consequently, the covariance between pixels x_j and xi is given by:

$$\sigma_{ij} = \rho^{\|x_i - x_j\|} \tag{6}$$

where ‖.‖ denotes the L_2 norm, and the covariance matrix of all *M* samples in N_x can be expressed as follows:

$$C = \begin{bmatrix} 1 & \sigma_{12} & \cdot & \cdot & \cdot & \sigma_{1M} \\ \sigma_{21} & 1 & \cdot & \cdot & \cdot & \sigma_{2M} \\ \cdot & \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & \cdot & & \cdot \\ \cdot & \cdot & & & \cdot & \cdot \\ \sigma_{M1} & \sigma_{M2} & \cdot & \cdot & \cdot & 1 \end{bmatrix} \tag{7}$$

Therefore, the covariance matrix of the transform coefficient vector F_x can be obtained using the following equation:

$$D = WCW' \tag{8}$$

Before quantization, the coefficients are decorrelated because, if the quantized samples are statistically independent, the information in numerical quantization is maximally preserved. The independence of the samples can be achieved using the whitening transformation, as given by the following equation:

$$G_x = V^T F_x \tag{9}$$

where *V* is an orthogonal matrix obtained from the Singular Value Decomposition (SVD) of matrix D, given by:

$$D = U \sum V^T \tag{10}$$

In the next step, G_x is quantized using the following equation:

$$q_j = \begin{cases} 1, & if\ g_j \geq 0 \\ 0, & otherwise \end{cases} \tag{11}$$

The quantized coefficients are represented as integer values between 0 and 255 using binary encoding:

$$b = \sum_{j=1}^{8} q_j 2^{j-1} \tag{12}$$

Finally, a histogram of these values is constructed for all pixels in the image and is used as a 256-dimensional feature vector for classification.

2.2.2. Feature Extraction Using the LBP Operator

The Local Binary Pattern (LBP) operator was first introduced as a rotation-invariant texture descriptor for grayscale images [15,16]. This operator calculates the values of the eight neighboring pixels in a 3×33 neighborhood for each central pixel by thresholding them against the central pixel's value. If a neighboring pixel's value is greater than or equal to the central pixel, it is assigned a label of 1; otherwise, it is assigned a label of 0.

Each of these labels is then multiplied by 2^i, where i represents the position of the label, ranging from 0 to 7. The summation of these weighted values results in a unique code for the given central pixel, which falls within the range of 0 to 255. Figure 2 illustrates an example of the LBP operator in action.

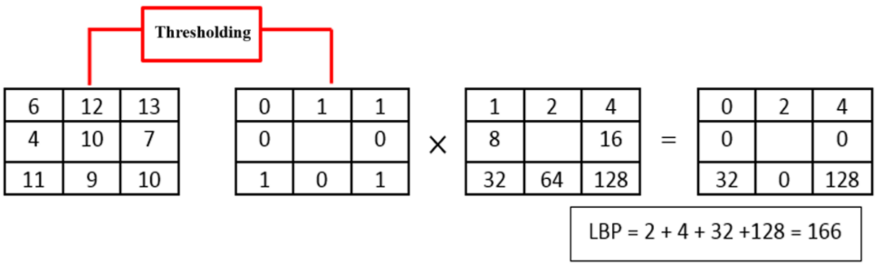

Fig. 2. Example of the LBP Operator

After labeling an image using the LBP operator, a histogram of these values is generated for all the pixels in the image.

2.2.3. Feature Dimensionality Reduction for LBP-Extracted Features

Given that most histogram bins corresponding to LBP values are zero, we employ the PCA-based dimensionality reduction algorithm to decrease dimensionality and improve feature accuracy. The steps of the PCA-based dimensionality reduction algorithm are as follows:

- **Step 1:** Subtract the mean from the data.
- **Step 2:** Compute the covariance matrix.
- **Step 3:** Compute eigenvectors and eigenvalues. According to linear algebra theorems, an $n \times n$ symmetric matrix has n independent eigenvectors and n corresponding eigenvalues. The eigenvalues indicate the degree of variance in the data along the corresponding eigenvectors, with

the eigenvector associated with the largest eigenvalue representing the principal component of the dataset.

- **Step 4:** Select principal components. The eigenvectors are sorted in descending order based on their eigenvalues. Consequently, data components are arranged from most to least significant, and the least significant components are eliminated to reduce dimensionality.
- **Step 5:** Compute the new transformed data. The obtained transformation matrix is multiplied by the data.

2.3. Classification

To identify the identity of an input user, we employ the k-nearest neighbors (k-NN) classifier. This method consists of two steps:

- **Step 1:** Compute the distance between the input sample and all training samples. In this study, we use the Canberra distance metric to calculate these distances. The Canberra distance formula is defined as follows:

$$d(p.q) = \sum_{i=1}^{n} \frac{|p_i - q_i|}{|p_i| + |q_i|} \tag{13}$$

- **Step 2:** Sorting the training samples based on distance and selecting the k-nearest neighbors: In this paper, we have used k=1.

3. SIMULATION RESULTS

To evaluate the performance of the proposed method, we used the USTB-1 database [17]. This database consists of 180 ear images from 60 individuals, with each individual having three images: a normal image, a slightly rotated image, and an image with different lighting conditions.

Figure 3 presents an example of images belonging to a single class from the USTB-1 database.

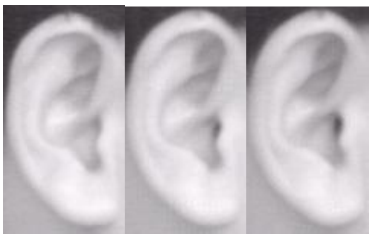

Fig. 3. An example of images belonging to one class from the USTB-1 database.

In the USTB-1 database, each individual has three ear images, including:

1. A normal image
2. An image with slight head rotation
3. An image with varying illumination

For our training and testing strategy:

- Training set: 120 images (2 images per person)
- Test set: 60 images (1 image per person)

Performance Comparison:

- LBP-based recognition accuracy: 23.33%
- LPQ-based recognition accuracy: 95%

When combining LBP and LPQ features, accuracy dropped to 88.33%, due to the presence of zero bins in the LBP histogram affecting Canberra distance calculations.

To mitigate this, we applied PCA-based dimensionality reduction on the LBP features before merging them with LPQ features. This boosted recognition accuracy to 98.33%.

These results are summarized in Figure 4.

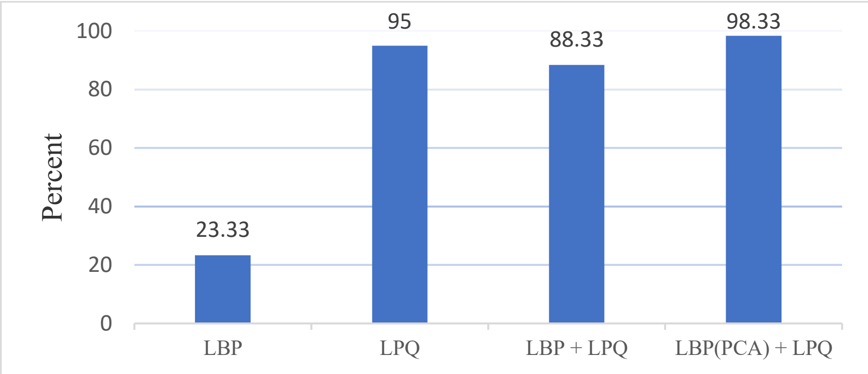

Fig. 4. Recognition rate in ear biometrics using the proposed method.

Additionally, the proposed method has been compared with several existing methods on the USTB-1 database, and the results are presented in Table 1. As can be observed, the proposed method achieves higher accuracy compared to the existing methods.

Table 1. Comparison of the proposed method with previous algorithms.

Method	Accuracy (%)
Zhang et al. (2005) [6]	88.33
Zhang et al. (2008) [8]	91.67
Yazdanpanah et al. (2011) [10]	93.33
Ghavami et al. (2016) [13]	97.15
Proposed Method	98.33

4. CONCLUSION

Identity recognition in biometrics has gained significant attention, particularly with advancements in image processing techniques. Among various biometric traits, ear recognition has emerged as a reliable method due to the unique structure of the human ear. This study reviewed existing research on ear-based identity recognition, with a focus on approaches utilizing Local Binary Patterns (LBP) and Phase Quantization techniques. The findings highlight the efficacy of these methods.

In this paper, we proposed a novel method for ear-based biometric identification, employing LBP and LPQ operators for feature extraction. To reduce the dimensionality of the feature vector, we applied Principal Component Analysis (PCA) to the LBP-extracted features. The proposed method was evaluated on the USTB-1 database, achieving an identification accuracy of 98.33%.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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