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IMPLEMENTING AND DESIGNING BIOMETRIC SYSTEM FOR DETECTION AND IDENTIFICATION WITHOUT LIMITATION OF HUMAN EAR

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ABSTRACT

In the current article, by designing and implementing an ear-based biometric system, ear recognition operations in images and identification with the human ear are performed automatically and without the need for user interaction. To design the system, in the ear detection step, in the main images of the database, the Image Ray Transform (IRT) algorithm is used, and also a method is proposed for normalization. In the identification stage, local tissue descriptors of Local Binary Pattern (LBP) and Binarised Statistical Image Features (BSIF), and Weber local descriptor (WLD) were used to extract the feature and the nearest neighbor k algorithm was used for decision making. The result of the accuracy of applying the binary pattern feature on the ear images is equal to 50%. The result of the accuracy of applying statistical properties on binary images is equal to 93.88% and the result of the accuracy of applying Weber local descriptor feature on ears images is equal to 60.05%. The method proposed in this paper improves the performance of the Weber local descriptor (WLD).

1. INTRODUCTION

Information security is one of the most significant subjects in today's society, which has become a disquiet for many experts as well as users with the spread of issues such as e-government and online sales. The most common methods of identification and authentication are passwords or text passwords. Experts are seeking safer ways, one of the most efficient of which is the use of biometric systems. Biometrics has emerged as a major area of security systems in the last decade [9]. Identification of human identity using physiological traits or behavioral characteristics that are unique and distinctive, robust, and measurable is called biometric [12]. The human ear is a new field of research related to the design of biometric systems. Many researchers have shown that the ear-based identification system is a suitable alternative to other biometric systems such as the face, fingerprint, and iris [1]. Numerous methods have been proposed to detect the ear in unrestricted images, most of which are based on the geometric and morphological properties of the ear. Among them, we can mention the method of ear detection using adjustable lines [10]. The chief problem is that, in this method, there is a need to interact with the user to determine the number of adjustable lines, which in the case of using this method, the detection work is not done completely automatically. Experts have also proposed a variety of methods for extracting features from ear images at the authentication stage [4]. But, these methods are not very resistant to changes in image rotation and brightness, and the systems do not operate completely automatically. In this research, we seek to design and implement a biometric system based on the human ear that automatically receives unrestricted images of the human ear and then uses the Image Ray Transform (IRT) method [2] to detect the ear area and in The authentication step also uses local texture descriptors such as local binary pattern (LBP) [11], Binarised Statistical Image Features (BSIF) [5] and Weber local descriptor (WLD) [8] to extract features to improve system identification. In section (2), the concepts and algorithms used in this research will be discussed and the implementation steps of the proposed method will be introduced. In section (3), first, the database used is introduced and then the numerical results and analysis and comparison of the results of testing the proposed method with other previous research will be described. The conclusion will be made in section (4).

2. PROPOSED METHOD

In this section, first, the applied algorithms are introduced, then the design and implementation steps of the proposed method will be described.

2-1-Applied algorithms:

2-1-1- Image Ray Transform (IRT):

Image ray transform is a novel way to enhance the structural features of images. This method uses the rules of optics to highlight the circular features in the image. Light emission can be simulated using beams or rays, a model that pays attention to the trajectory. Light rays travel in the environment and may be refracted or reflected at the boundaries of other media [2]. The image ray transform method emphasizes features that have a higher brightness than their neighbors. In this method, the input image is first converted to a glass block matrix whose arrays represent the refractive index of each block. In the next step, a random beam is generated in one of the pixels of the image glass block matrix. After generating a random beam, this beam moves in the glass block pixels according to the rules of optics and the refractive index of each pixel and the direction and angle of each beam, which may be refracted each time and go into the next pixel or general reflection and remain inside the current pixel. Each unique beam travels only one pixel once.

2-1-2- Local Binary Pattern (LBP):

The local texture descriptor LBP is defined as an operator on the grayscale texture, based on a general definition of texture in a local neighborhood. In this method, pixel P is considered as the current pixel, and its area with radius R is considered as neighboring pixels of pixel P [11]. Regarding the brightness of the P pixel, a threshold is considered and all the pixels in the circle area with radius R and center P are taken to the binary space. This binary sub-image is then doubled and the sum of the individual brightness of the neighboring pixels is considered as the new value for the P pixel. This process is done for all image pixels to extract the LBP attribute of the image [11].

2-1-3- Binarised Statistical Image Features (BSIF):

The BSIF descriptor is used to identify the face and classify the texture. The BSIF descriptor encodes each pixel of the given biometric image in terms of binary strings based on the filtered response before training, and this solution provides acceptable results for comparing texture in natural images in addition to face recognition. For this purpose, researchers also use the BSIF descriptor to identify the ear [5]. To determine the texture properties of biometric images, BSIF properties are obtained as a binary pixel histogram for each sub-area of the image. In the BSIF descriptor, two parameters, filter size, and string length are very important.

2-1-4-Weber Local Descriptor (WLD):

According to Weber's law [8], Weber's local descriptor is proposed to classify the texture of the image. The WLD descriptor consists of two components: differential excitation and orientation. The differential excitation is calculated for each pixel. This ratio is between the two terms, the brightness of the current pixel and the difference in the relative brightness of the current pixel against its neighbors. Furthermore, the direction of the current pixel gradient is also calculated [3]. The WLD descriptor extracts the edges of the image despite heavy noise. The WLD descriptor has performed well in the field of tissue classification and facial recognition [3] and facial detection [6].

2-1-5- K-nearest neighbors (k-NN) algorithm:

It is a sample-based classifier that is well known and widely used. The K-nearest neighbor algorithm is a simple algorithm that considers all existing samples and classifies the new sample according to its similarity to existing samples. This algorithm uses the distance or similarity criterion to classify a new sample, and based on this criterion, K identifies the nearest neighbor of the new sample and then uses the voting between this neighbor K to determine the class of the new sample. The Majority vote is the most common method.

2-2-Implementation:

As shown in Figure (2-1), the implementation process consists of two main parts, which are:

Ear detection block and ear identification block.

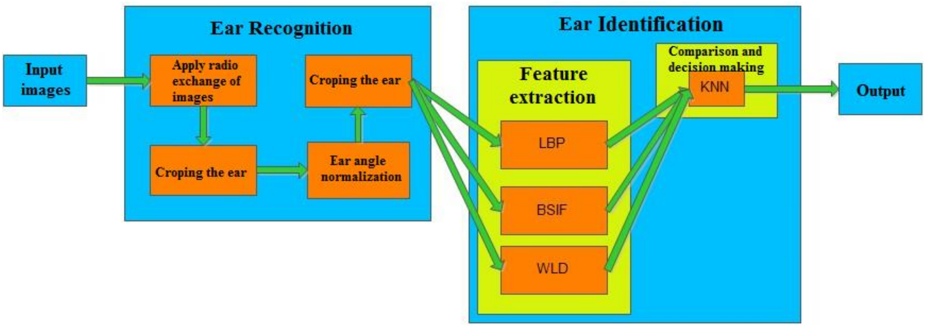

Figure 1-2: Implementation steps

Each section will be described separately below.

2-2-1-Ear detection block.

In this block, we first cropped the ear area to the input image by applying the image ray transform (IRT) algorithm to the input image. To normalize the angle of the ear, we first determine the rotation angle. For this end, first, we extract the edges of the image and then we extract the skeleton of the image using morphological concepts. After this step, the minimum and maximum points of the image are determined and the slope of the line joining these points, which is the angle of our rotation, is calculated. After this step, the normalized image is cropped.

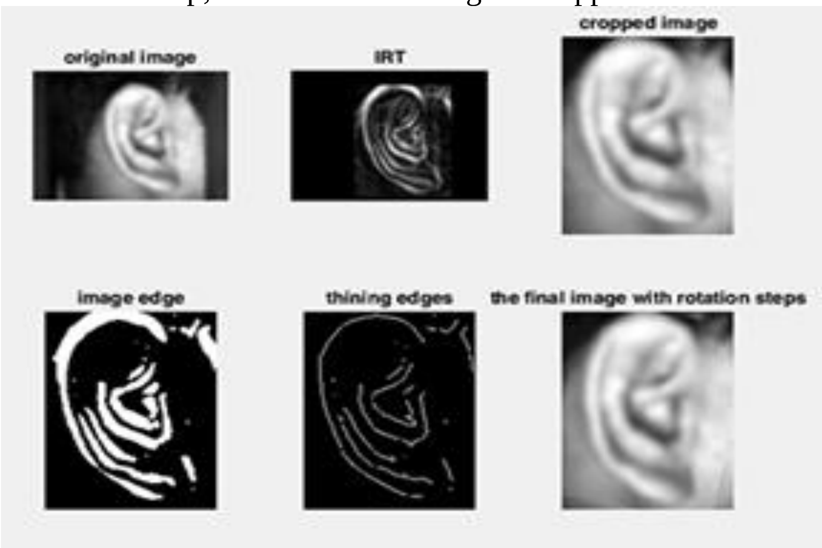

Figure 2-2: Ear detection stage

2-2-2-Ear identification block

In this step, the output of the ear detection block is used. To improve the detection operation, we extract the LBP, BSIF, and WLD properties of the images, respectively.

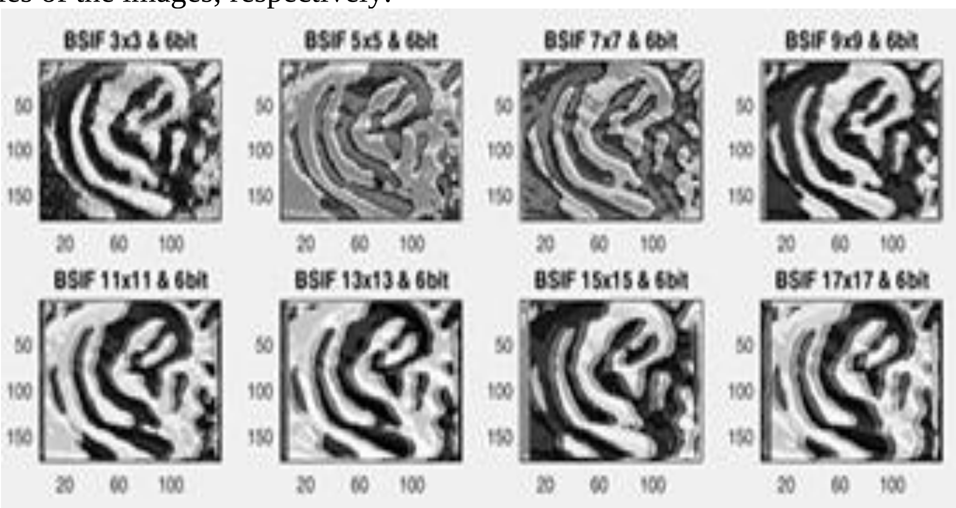

Figure 2-3: Output of BSIF application on the ear image

3- TEST RESULTS

3-1-Database:

The IIT Delhi Database is a standard database that includes ear images of 221 people between the ages of 14 and 28. At least 3 ear images have been taken from each person at the same distance, the total number of main images in this database is 471. This database has two subsets, one of which includes ear images with a resolution of 180 x 50 pixels, and the other includes ear images with a resolution of 204 x 272 pixels. Images with a resolution of 180 x 5, are cropped and normalized images of the main ear (with a resolution of 274 x 204) images.

3-2-Numerical results:

In a study conducted by Hezil and Boukrouche in 2017 [7], normalized images from the IIT database were used. Hezil and Boukrouche's research focuses only on the problem of identification using the multifunctional biometric system of the ear and the effect of palms. For this reason, they have used normalized images of the database. In their research, the best accuracy of 98.90% was obtained by applying a BSIF descriptive of local texture, with a filter size of 17*17 and a string length of 10 and 11 bits. Likewise in that study, the accuracy results obtained from the application of local tissue descriptors LBP and WLD were equal to 62.44% and 55.20%, respectively.

In the current study, since the goal is to design a human ear-based biometric system with minimal user involvement, we used the original images in the IIT database with a resolution of 274 x 204 pixels.

In the suggested method in this research, to extract the BSIF feature of images, filters of 3*3, 5*5, 7*7, 9*9, 11*11, 13*13, 15*15, and 17*17 were tested and evaluated along with the 5, 6, 7, 8 and 9-bit strings. The result of the accuracy of applying the BSIF feature on the ear images with the proposed method is shown in Table (3-1). Similarly, the results of the accuracy of applying LBP and WLD properties on ear images with the proposed method are shown in Table (2-3).

Table 3-1: Results of descriptive applications of BSIF local texture in the presented method

BSIF (ear) Euclidean	3*3	5*5	7*7	9*9	11*11	13*13	15*15	17*17
5 (bit)	91.38	84.72	84.16	90	89.72	91.66	90.27	88.05
6 (bit)	93.88	86.11	82.22	88.88	85.27	85	83.05	86.66
7 (bit)	85.27	82.5	80.83	81.94	86.38	83.88	84.16	83.05
8 (bit)	73.05	78.05	78.6	83.05	83.88	82.22	80.55	81.38
9 (bit)	/	68.03	69.72	75.27	78.88	80	81.38	80.55
10 (bit)	/	67.22	75.83	73.88	73.61	77.77	75	80
11 (bit)	/	66.94	70.55	73.61	75.55	72.77	75.27	72.77
12 (bit)	/	61.66	65	74.16	76.94	78.05	73.33	78.33

Table 2-3: Results of LBP and WLD applications on ear images by presentation method

	ear
LBP	50
WLD	60.05

Table 3-3: Comparison of research results in the field of biometric systems based on the human ear

References	Feature Extraction	Classifier	Recognition Rate
Kumar [13]	Shape feature	K-NN	30.62
Hurley [14]	Force field transform	K-NN	66.67
Kumar [13]	Gaboor phase	K-NN	84.46
Our approach	IRT+BSIF descriptor	K-NN	93.88
Hezil [7]	BSIF descriptor	K-NN	98.90

3-3-Analysis of results:

As can be seen in Tables (3-1) and (3-2), in the method presented in this research, via applying a BSIF descriptive of local texture to the images, with a filter size of 3*3 as well as a string length of 6 bits, the highest accuracy of 93.88% has been obtained. In Hezil and Boukrouche's research, by applying the same descriptor to the images of human-normalized ears, the highest accuracy with the filter size of 17*17 and the length of 10 and 11-bit strings, is equal to 98.90%. Nonetheless, all components of the algorithms are considered the same.

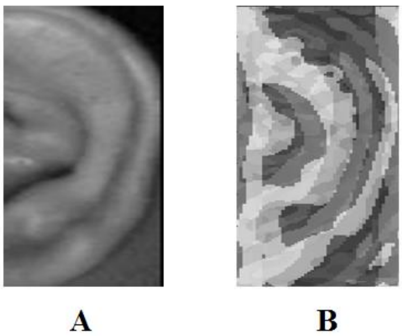

Figure 3-1: Feature extraction with BSIF, A) human cropped and normalized image, B) BSIF application on the ear image in Hezil and Boukrouche method

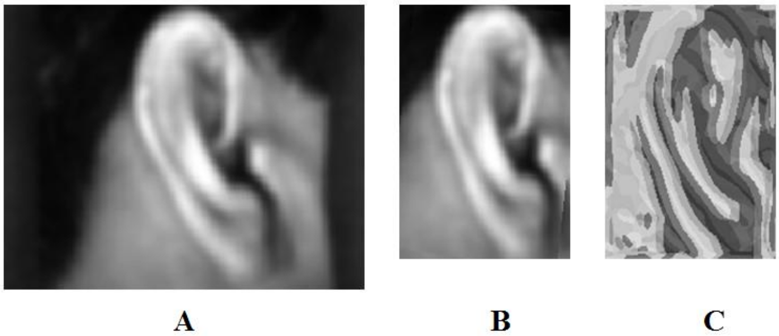

Figure 3-2: Feature extraction with BSIF, a) Original image, b) Cropped and normalized image with the proposed method, c) Apply BSIF on the ear image in the proposed method

As can be seen in Figures (3-1) and (3-2), in the images obtained by the proposed normalization method, some areas have almost the same texture areas, which have been cropped and normalized by humans. The presence of these areas has led to the poor performance of the BSIF local tissue descriptor in the presentation method. But the advantage of the proposed method is that the work is done automatically without the need for user interaction.

The result of the accuracy of the WLD Descriptive of local texture application on the ear images with the proposed method, as can be seen in Table (3-2), is equal to 60.05%. While in Hezil and Boukrouche's research, by applying the same descriptor on human normalized images, this accuracy has been obtained as 55.20%. This indicates that the proposed method works better than the previous research method.

As can be seen in Table 3-3, the method presented in this study has higher accuracy than other human ear-based biometric systems.

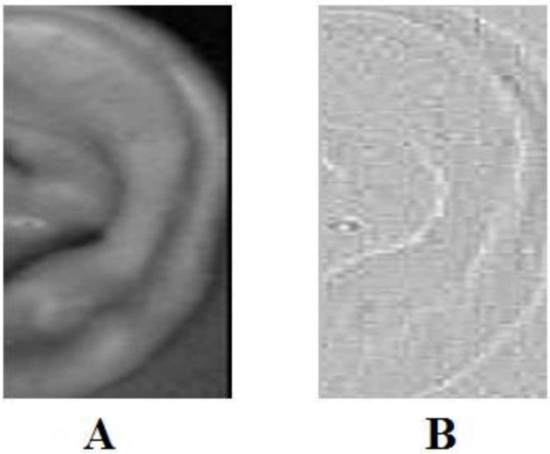

Figure 3-3: Feature extraction with WLD, A) image cropped and normalized by human, B) WLD application on the ear image in Hezil and Boukrouche method

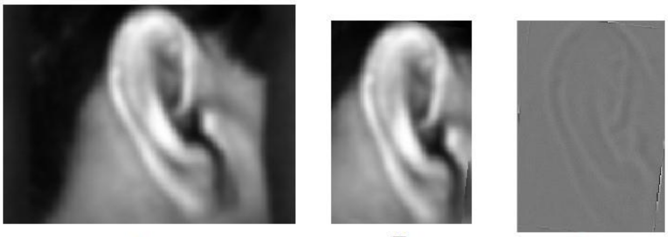

Figure 3-4: Feature extraction with WLD, A) main image, B) cropped and normalized image with the proposed method, C) application of WLD on the ear image in the proposed method

As shown in Figures (3-3) and (3-4), the WLD local texture descriptor can extract the edges of the image well, and because the ear has more details in the proposed method, and the edges are not cropped, so the WLD performs better in the proposed method.

4 - CONCLUSION

In most biometric systems research, the problem of ear recognition in images and ear-based identification is viewed as two distinct categories, and the impact of these two categories on each other is overlooked. In this research, a method was offered that these two issues are located next to each other, and the detection and identification operations are performed automatically and without the need for user interaction.

In the proposed method, image ray transform (IRT) algorithm for ear area detection and local tissue descriptor algorithms, such as local binary pattern (LBP), binarised statistical image features (BSIF), and weber local descriptor (WLD), for feature extraction were used to improve ear recognition function.

Comparing the results of the implementation of the proposed method with previous research methods, we found that the proposed system performs poorly with the LBP and BSIF features, but performs better with the WLD feature. To investigate this, we evaluated the database images, taking into account that the implementation and database conditions were the same. In the methods in which the ear images were normalized by humans, some areas of the ear were cropped, and the absence of these pixels improves the performance of the LBP and BSIF feature extraction algorithms. However, the presence of these pixels, which spot the border between the ear and the background, improves the performance of the WLD algorithm. This is because the WLD recognizes the edges of the image well. Consequently, if we consider the category of detection and identification in biometric systems together, we will understand the needs of these two categories to each other.

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