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Automatic Ear Segmentation Using Banana Wavelets and Hough Transform

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ABSTRACT

Automatic Ear Detection from a side face image is an essential preprocessing step in many applications including Ear Biometrics. Perfect, precise and fast ear detection for real-time applications has high impact in the efficiency of such biometric systems. The proposed ear detection method takes advantage of the curvedness of the ear as a feature for the experimentation. The proposed system uses Banana Wavelets and Hough Transform algorithm to automatically segment and detect the ear region. The striking feature of the proposed system is that it doesn't need any template or training data for detecting the ear region. The experimental results demonstrate the effectiveness of the approach. The proposed ear detection and verification methods were successfully tested with 300 images and are found giving an accuracy of 83%.

KEYWORDS Biometrics, Ear Detection, Banana Wavelets, Hough Transform.

1. INTRODUCTION

Biometrics is the automated recognition of individuals based on their biological or behavioral characteristics. The most recent decade has seen an improved focus on secured forms of identification in security governance that led to a massive growth and consistency in the application of biometric technologies globally.

Ears are relatively new class of stable biometrics that is invariant from infancy to early old age. It is not affected with facial expression, cosmetics and eyewear. The ear has a lot of desirable attributes such as universality, uniqueness and permanence [1, 12]. Though there exists many common human traits like fingerprint, face, voice and iris which can be used as biometrics, there still remains some largely unsolved issues especially in wide variety of imaging (e.g. lighting, shadows, scale, and transformation). A suggested alternative to this is ear biometrics. It has been observed that finding two ears which are completely identical is almost impossible and ear does not change much with time, unlike face. Furthermore, ear satisfies all the properties that should be possessed by a biometric [2, 3, 12]. Ear, is distinguished by the appearance of the outer ear, lobes and bone structures which are specific unique, rich and stable structures that assist in human identification [1, 2]. An ear can be captured without any knowledge or consent of the person under examination. It also does not suffer from changes in facial expression [1]. These properties make ears appropriate as a biometric identifier. As a result, the passive ear biometric is appropriate for security, surveillance, access control and monitoring applications.

Automatic ear detection is a mandatory step in the automatic ear recognition system. At the same time, detection of ear from a profile face image is one of the challenging problems. This is because of the fact that ear image can vary in appearance under different viewing angles. The size of the ear is not same in all face images. The performance of the whole recognition system depends upon the accuracy of the automatic detection. The paper proposes an automatic ear detection method using a wavelet transform approach called Banana Wavelets which exploits the curved structure of the ear [2] and further implement the Circular Hough Transform to identify the elliptical shape.

This paper is structured as follows. Section 2 gives a review of the related work. Section 3 gives a brief background on banana wavelet filters followed by Circular Hough Transform. Section 4 describes our proposed technique of automatic ear detection. The experiments and the analysis of the results of automatic detection and segmentation are provided in section 5.

2. REVIEW OF THE RELATED WORK

Automatic localization of the ear from the profile image is a requisite step for ear detection. It therefore appears appropriate to investigate a technique which depends on the general structure of the ear. [1].

In the literature, there are very few techniques available for automatic ear detection [1, 2, 6, 8, 9, and 14]. Most of the ear recognition methods were carried out without a fully automated method for ear detection. Yet automated schemes have recently been proposed for ear detection [4, 5, 6] and 3D [7, 8] ear detection. The common approach is the ear template method [2, 5, 8, 9, 10, and 13] which is manually performed by cropping the ears of different size from the side face images. The template matching is performed for the detection and recognition. In the real time scenario, especially under surveillance, the ear occurs in various sizes as people are not always keeping the same distance from the camera. Thus the predestinated templates are not sufficient to handle the recognition system successfully. In addition, the detection of ear using templates of various sizes and selection of the proper template either right or left is a tedious task. The accuracy of the system depends on the template chosen for the comparison.

Ajay Kumar.et. al [18] has explained an automatic segmentation of ear using morphological operations. A mask is generated and multiplied with image to obtain the segmented ear. Islam et al. [4] modified the cascaded AdaBoost approach to detect the ear from 2D profile images in a learning method by using a training data of ear images. The system reported very good results on large size databases with very low false positive rate and high speed and even robust in the presence of occlusion or noise. But, the system will not detect the ear, if the ear image is rotated with the respect to the training data or if its appearance is different from the ears in the training data. Forming a database with all variant orientations will require much storage than an established one.

In [11] Ansari and Gupta have proposed a system which considers the outer helix and neighboring structures to identify the ear. Though it is a simple method, the system depends upon the image quality as it is finding the edges of the ear. A new method using image ray transforms were used in [7] by Cummings et.al. The method was an effective technique with high accuracy of 99.6% for ear enrolment. The ray transform method responded for tubular features in the profile face. Hence response of this method is not much effective in the images where people wear spectacles.

The curved feature of ear can be considered as a sound feature for detection. Ibrahim.et.al [2] employed a bank of banana wavelets, which are generalized Gabor wavelets, to extract curvilinear structures. In addition to the frequency and orientation, banana wavelets are also characterized with properties associated with the bending and curvature of the filter. The method in [2] uses banana filters. However, the method uses a template matching algorithm for ear detection where the performance is based upon the manual selection of the template [2]. The system also acts poor in the cases of rotated or translated profile face images.

The proposed work focuses on the automatic ear segmentation and detection using banana wavelets to identify the curved edges. The ear portion is an image region that generally contain features which are similar to those of banana wavelets especially in the region of the helix (the uppermost part of the ear) and the tragus (which are the lower parts).Such curved regions are identified using Banana Wavelets. The accuracy of the ear detection is improved using Hough transform as the circular regions can be detected using Circular Hough Transform.

The next section discusses the basics of Banana Wavelets.

3. BANANA WAVELETS

Wavelets are now being used widely in various computer vision applications. Banana wavelets are a generalization of Gabor Wavelets and are localized filters derived from a mother wavelet, mostly suited to curvilinear structures[2, 6]. The table gives a comparison of Gabor and Banana filters in different orientations.

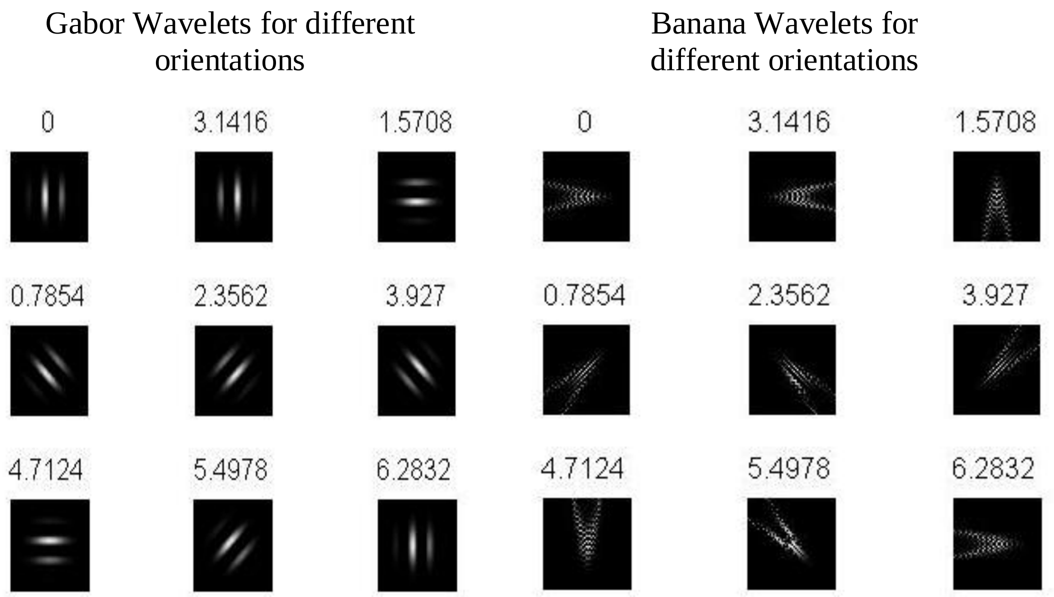


Fig 1: Gabor and Banana Wavelets

A banana wavelet B^b is parameterized by a vector **b** of four variables, i.e. **b** =(*f*, θ, *c*, *s*) where *f*, θ, *c* and *s* are the frequency, orientation, curvature, and size/elongation respectively[1]. This filter consists of two components i) a rotated and curved complex wave function $F^b(x, y)$ and ii) a Gaussian $G^b(x, y)$ function rotated and curved in the same way as $F^b(x, y)$

$$B^b(x,y) = \gamma G^b\ (x,y).(F^b(x,y) - DC^b) \tag{1}$$

Where

$$G^b(x,y) = \exp\ (\frac{f^2}{2}.\left(\frac{x + c.y^2}{{\sigma_x}^2}\right)^2 + \frac{y^2}{{\sigma_y}^2.s^2} \tag{2}$$

$$F^b(x,y) = exp\left(i.f.(x + c.y^2)\right) \tag{3}$$

$$x = x.cos\ \theta + y.sin\theta \tag{4}$$

$$y = -x.sin\theta + y.cos\theta \tag{5}$$

$$DC^b = \int \frac{G^b(x,y).F^b(x,y)}{G^b(x,y)} = e^{\sigma/2} \tag{6}$$

γ is a constant, chosen empirically, σ_x and σ_y are the scales of the Gaussian filter in the *x* and *y* directions respectively, and DC^{b} is the bias of the banana wavelets.

Features extracted from the image using banana wavelet transform describe both spatial frequency and curvilinear structure present in the image. The convolution of an image with complex banana filters with various frequencies, orientations, curvatures, and sizes, captures the local structure of the image [2].The magnitude of the filter responses by convolving a banana wavelet B with an image I will give maximum values at location of the curves. The location having the maximum values will form the candidate regions or regions of interest. In the profile face region, the major curved portions include the nose region and the ear.

Circular Hough Transform

The Hough transform is a feature extraction technique used in different fields like image analysis, computer vision, and digital image processing [15]. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. Hough Transform for Circle Detection detects the circular shapes in the image.

The equation of the a circle is

$$r^2 = (x-a)^2 + (y-b)^2 \tag{7}$$

Here a, b represent the coordinates for the center, and r is the radius of the circle. The parametric representation of this circle is

$$x = a + r\cos\theta \tag{8}$$

$$y = b + r\sin\theta \tag{9}$$

4. PROPOSED AUTOMATIC EAR DETECTION SYSTEM

This paper presents an automatic ear detection and segmentation method for the personal identification using 2D ear image. The proposed system executes precise approach for the segmentation of exact region of interest i.e. right or left ear portion, from the acquired gray level or color side ear images. The steps of the proposed approach are shown in Fig 2.

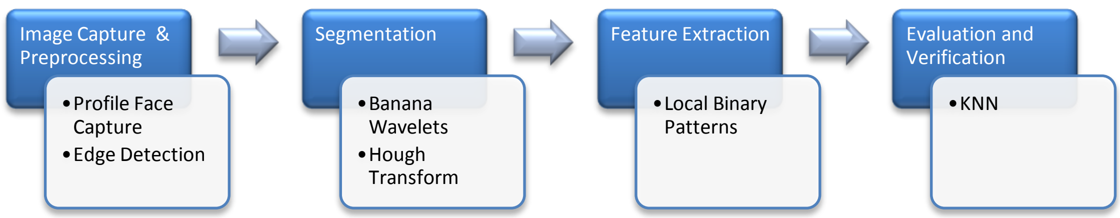


Fig 2: The steps of Automatic Ear Segmentation & Detection System

Ear has curvilinear structures such as the helix, anti-helix and inter-tragic notch [2]. The proposed system is initiated with the acquisition of profile face image which is captured using camera. The region of interest from the preprocessed image is obtained by convolving the responses of wavelet transform with the gradient image. The convolution of the image with complex banana filters is evaluated with different orientations and curvatures which helps to capture the local structure points of the input image[2]. The transform strongly responds to the curvatures which help the detection of the most curved areas of the profile face region. The input profile face image and the response magnitudes, which are calculated by convolving the input image with different curvatures and different orientations in banana wavelets is shown in Fig. 3. In the output figure(c), white pixels represent high values in the response magnitudes. The candidate region includes the curved structures of the face. A position of interest is selected by considering the value of the pixels greater than the global threshold level.

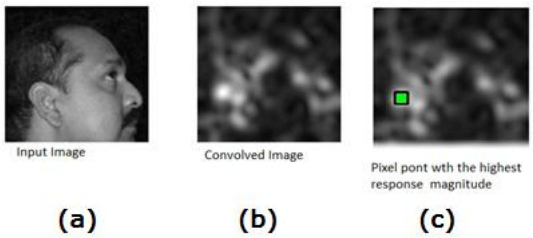


Fig 3: Profile face image convolved with banana wavelets

The banana wavelets respond to multiple regions as there are more than one curved regions in our face. Ear region has a circular/elliptical curved structure. A Hough Transform algorithm is used to detect such structures in the image [5, 8]. In the proposed method, the Hough transform with radii of varying range is opted. The varying radii measures for the Circular Hough Transform are used as there are probabilities of different size of ears in the input images. The coordinates of the circle with highest count is considered as the peak point and the image section is segmented which hold the ear portion.

The segmented portion of the input image is verified to find if the portion detected by the algorithm is originally an ear or not. The Local Binary Pattern features of the segmented image are compared with the LBP features of different ear templates stored in the database. Local Binary Patterns (LBP) is the texture descriptors that perfectly summarize the local structures of an image efficiently [14]. The verification is performed using the KNN algorithm.

5. EXPERIMENTS AND ANALYSIS OF RESULTS

In this proposed system, we have used Banana Wavelets together with the Hough Transform for the automatic ear detection and segmentation. Details of the data set and results are presented below.

Dataset: Two different test sets of facial images taken under different illumination conditions and different quality.

Dataset 1: 300 images from CMU database

Dataset 2: Database containing 50 images captured using Canon SX10 created as part of this work.

Experiment:

In the initial stage of experiment where banana wavelets are involved, the response magnitude of 5 different curvatures and 5 orientations were convolved with the input image. The output image is then fed as input to the Hough transform which gives the segmented image with the ear region. The LBP features of the automated segmented region are extracted as the feature vector which is compared with the trained ear features. 400 ear images of varying ear shapes are trained and the feature vector is stored in the database. The LBP features are considered for training and testing of the images. Two classes are considered for the classification: Class Ear and Class Non Ear. The KNN classifier is used to classify the segmented portion of the image to class Ear or Non Ear class, which helps to verify whether the automatically segmented region is actually the ear region or not. The automated system gave an accuracy of 83%.

The proposed method does not need any trained data or template to perform the matching. Thus the possibility of obtaining wrong output due to wrong template choice is the least. Moreover ear can be detected from images, at any angle, with a clear helix curve. The images can be taken from different angles with ear helix edges visible. Fig 4 shows images taken from different angles and the segmented area. The Hough Transform can be used to identify the ear [8]. But more accurate results were obtained when considering the banana wavelets as a method for finding the curvature areas.

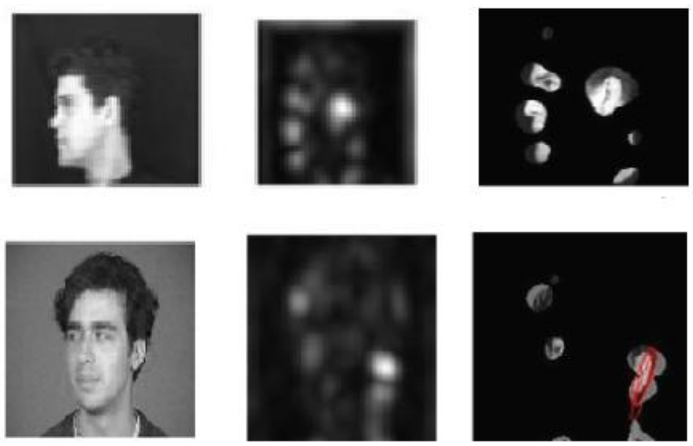


Fig 4: Images taken from different angles and the segmented area.

Parameter Settings for the Banana Wavelets
In the proposed method, 5 orientations and 5 curvatures were considered. Table 1 depicts the angle values and curvatures

Table 1: Angles and Curvatures in the experiment

Angle	Curvature
0	-0.5
pi/4	-0.1
pi/2	0
3*pi/4	.1
pi	0.5

The proposed method is implemented and tested. For evaluation purpose, the testing is done manually – to check whether the segmented region contains ear or not. In addition to the proposed method, the segmentation is carried out with Gabor Wavelets, Skin Segmentation and Gabor Wavelet as well as Banana Wavelet and Template Matching. The results are shown in Table 2. As it is evident from the table, Banana wavelet and template matching gives the best performance but it is semi automatic and requires human intervention for the detection. Out of the other three methods, which are automatic, the proposed system outperforms the other two with a huge margin.

Table 2: Comparison of Different Ear Segmentation Methods implemented

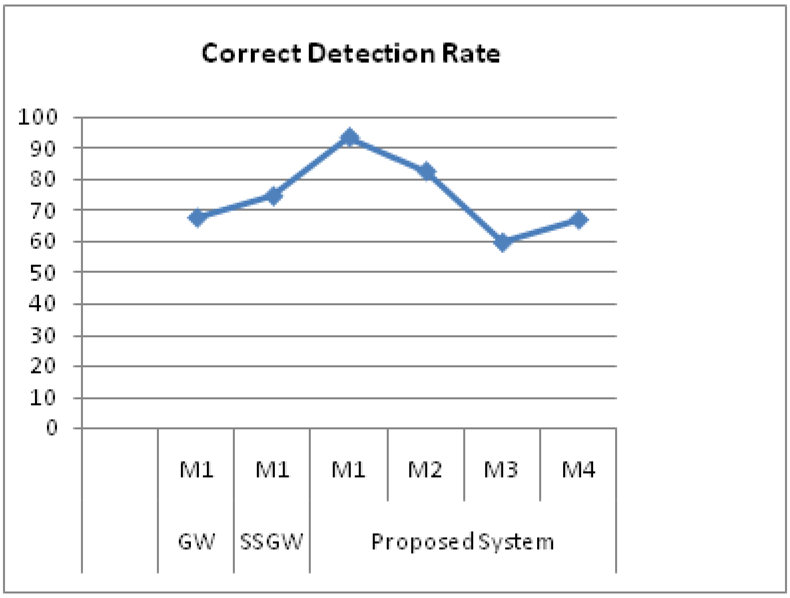
Segmentation Method Used	Ear Detection Accuracy %
Gabor Wavelet	68
Skin Segmentation & Gabor Wavelet	75
Banana Wavelet and Template Matching (Semi Automatic)	99
Proposed System-Banana Wavelets with Hough Transform (Automatic)	94

In addition to the manual testing the efficiency of the proposed method is measured with an automatically classification technique. For this the features such as LBP, Gabor and Shape segmented region are extracted and is used for classification. Euclidean Distance, KNN and SVM are employed for classification. The results given with LBP features together with KNN are much closer to the results of manual testing. Table 3 summarizes the results obtained.

Table 3: Comparison of Different Recognition Methods implemented

Features Extracted	Classification Used	Efficiency (%)
LBP	Euclidean	80.2
	KNN	83
	SVM	64
Gabor	Euclidean	65
	KNN	60
	SVM	56
Shape	Euclidean	64
	KNN	67.4
	SVM	60.2

From the manual as well as automatic, it is evident that the proposed banana wavelet based method outperforms the other automated ear detection methods. Figure 5 depicts the performance of the proposed method.



Method	Description
GW	Gabor Wavelet
SS GW	Skin Segmentation and Gabor Wavelet
M1	Manual verification
M2	LBP and KNN
M3	Gabor and KNN
M4	Shape and KNN

Graph Showing the Detection Rate against various segmentation methods.

When we consider the complexity of the algorithm, the proposed method is more complex than the other two automated methods. A detailed analysis in terms of the complexity as well as execution time required to be carried out to further establish the proposed method as an efficient automated algorithm for ear detection.

6 CONCLUSION

This paper reveals that banana wavelets can be used to find the ear from head profile images for biometric purpose. The proposed system detects human's ear without any learning procedure or statement of previous knowledge about the input image. It does not need any human intervention as used in other similar systems, hence can be used successfully in a fully automated ear recognition system. The template matching method which is a common procedure in ear biometric systems are also avoided in this proposed method. The performance of the banana wavelets technique is compared with that of Gabor wavelets technique which shows that banana wavelets can capture the curved structures better than Gabor wavelets. Much accurate results could be obtained when circular Hough transform is applied to the system. The LBP features of the obtained result are verified with LBP features of trained ear images using KNN classification. Thus the technique proposed here is fully automated and does not require any manual assistance to detect the ear from the profile face image.

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