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Ear Detection Techniques In Biometrics: A Survey

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Abstract

Due to an ever-growing need to automatically authenticate individuals, biometrics remained an active field of research over the course of the last decade. Biometric has been proved to be a reliable means of enforcing constraint in a security sensitive environment. Identifying the people through their ear is the emerging trend in the modern era. Human ear is the unique and clearly visible trait that is permanent for his/her lifetime. The increasing age of human being affects very less on the ear. Detection and recognition are the two major components of an automatic biometrics system. Ear detection is a critical component since the errors in this stage can undermine the utility of the biometric system. This paper provides a detailed survey of research conducted in ear detection and recognition. It provides an up-to-date review of the existing literature revealing the current state-of-art for not only those who are working in this area but also for those who might wish to exploit this new approach.

Keywords: Biometric, Authentication, Ear Detection, Recognition, Edge, Ear Recognition System.

1. INTRODUCTION
Nowadays there is emerging need to automatically authenticate the humans. Due to this, biometrics has become the active research field of modern era. Biometrics is the automated

A. S. Falohun, W. O. Ismaila, B. O. Makinde, E. O. Omidiora, J. A. Awokola & O. A. Odeniyi

procedure to recognize a human being by using physical features such as face, iris, fingerprints, ear, palm and voice or behavioral features [1] or behavioural features like gait, keystroke pattern etc. [2]. Ear is a viable new class of biometrics since ears have desirable properties such as universality, uniqueness and permanence. The ear has certain advantages over other biometrics. For example, ear is rich in features, it is a stable structure which does not change with the age. It does not change its shape with facial expressions. Furthermore, the ear is larger in size compared to fingerprints and can be easily captured and does not require as much control during image acquisition as other biometrics although sometimes it can be hidden with hair and earrings [3]. It has fixed background. For face recognition, when an image is a side face image, only the ear offers a unique feature from which a person can be identified. Human ear detection is the first task of a human ear recognition system and its performance significantly affects the overall quality of the system [4]. Ear recognition is useful for person identification when an image of a side face is available. This paper includes the survey of the current research work done in the area of ear detection.

2. EAR DETECTION
The first and foremost stage involves localizing the position of the ear in an image. Ear detection is a critical component since the errors in this stage can undermine the utility of the biometric system [5]. This section summarizes the state of the art in automatic ear detection in 2D and 3D images respectively. Basically all ear detection approaches are relying on mutual properties of the ears morphology, like the occurrence of certain characteristic edges or frequency patterns [20].

2.1 Computer-Assisted Ear Segmentation
It is semi-automated methods which require user-defined landmarks specified on an image, and then ear segmentation is automated from that point onward.

a. [6] used a two-line landmark, with one line along the border between the ear and the face, and the other from the top of the ear to the bottom, in order to detect the ear region.

b. [7] proposed a modified snake algorithm and ovoid model technique. This technique requires the user to manually draw an approximated ear contour which is then used for estimating the ovoid model parameters for matching.

c. [8] presented an untrained ear recognition framework. To this end, a CNN-based solution for ear normalization and description was developed. It fused learned and state-of-the-art handcrafted features to improve recognition. The method presented a two-stage landmark detector that operated under untrained scenarios, and used the results generated to perform geometric image normalization that boosted the performance of all evaluated descriptors.

d. [9] presented a new algorithm for ear recognition based on geometrical features extraction like (shape, mean, centroid and Euclidean distance between pixels). A pre-processing phase was made by making all images into the same size, then snake model was used to detect the ear and median filter for noise removal. The experimental results showed that the proposed approach gave better results and obtained overall accuracy of almost 98%.

e. [10] proposed an ear biometric system in which the ear region was detected by locating the landmarks containing the ear pit and the tip of the nose. Using the cropped region, a breed ICP algorithm was used for 3D ear recognition. A modified ICP matching algorithm was then employed.

f. [11] proposed an ear detection method that was invariant to background and pose with the use of Snakes as active contour model. The proposed method encompassed two stages, namely, Snake-based Background Removal (SBR) and Snake-based Ear Localization (SEL). SBR was used to remove the background from a face image, and, thereafter, SEL was used to localize the ear. However, its computational time of 3.86 s per image could not be ignored for an ear detection system.

A. S. Falohun, W. O. Ismaila, B. O. Makinde, E. O. Omidiora, J. A. Awokola & O. A. Odeniyi

2.2 Template Matching Techniques

a. [12] located the ear using deformable contours on a Gaussian pyramid representation of the image gradient. Then edges were computed using the Canny operator, and edge relaxation was used to form larger curve segments, after which the remaining small curve segments were removed.

b. [13] also used a template matching technique for detection. They used both a hierarchical pyramid and sequential similarity computation to speed up the detection of the ear from 2D images.

c. [14] in the context of 3D ear detection, used a model-based (template matching) technique for ear detection. The model template was represented by an averaged histogram of shape index. The detection was a four-step process: edge detection and thresholding, image dilation, connected component labeling, and template matching.

d. [15] used outer helix curves of ears moving parallel to each other as features for localizing the ear in an image. Using the Canny edge detector, edges were extracted from the whole image. These edges were segmented into convex and concave edges. From these segmented edges, expected outer helix edges were determined. A database of 700 side faces was assembled and an accuracy of approximately 93% was reported.

e. [16] propose another edge-based ear detection approach in the similitude of fingerprint recognition techniques. A classifier with orientation pattern was trained using previously computed ear images. Like other naive classifiers, the method lacked robustness against rotation and scale. Additionally, it was reported that the classifier is likely to fail under large pose variations, because this will affect the appearance of the orientation pattern.

f. [17] presented an edge detection based method where the nose tip detection is very important because in this method ear detection was based on distance estimation between the nose tip and the ear.. An accuracy of 80% was achieved on CVL database.

g. [18] presented also a template based where the template has to be recreated for different datasets otherwise it degrades the performance of detection. Instead of moving template over the entire image, it is moved over the region which has higher probability to contain ear then it takes less detection time. An accuracy of 70% was achieved on CVL database.

h. [19] proposed edge connectivity for ear recognition on 3D images. Instead of edges, discontinuities in the depth map were used for extracting the initial edge image and later, the connectivity graph. The experiments utilized the 3D representations of the subsets in UND-J2 database and a detection rate of 99.38% was obtained. The detection rate of the graph-based approach was not influenced by rotation and scale.

i. [20] proposed a shape-based ear localization approach. The idea was based on using a predefined binary ear template that was matched to ear contours in a given edge image. To cope with changes in ear shapes and sizes, the template was allowed to deform. The dynamic programming search algorithm was used to accomplish the matching process.

2.3 Shape Based Techniques

a. [21] developed a shape-model-based technique for locating human ears in side face range images where the ear shape model is represented by a set of discrete 3D vertices corresponding to the helix and anti-helix parts. They started by locating the edge segments and grouping them into different clusters that are potential ear candidates. For each cluster, the ear shaped model was registered with the edges. The region with the minimum mean registration error was declared to be the detected ear region. Based on 52 subjects from the UCR database, with 6 images per subject, a 92.6% detection rate was achieved.

b. [22] enrolled the ear based by finding the elliptical shape of the ear using a Hough Transform (HT). A 100% detection rate was achieved using the XM2VTS face profile database consisting of 252 images from 63 subjects, and 91% using the UND, collection F, database.

c. [23] introduced a novel shape-based feature set, termed the Histograms of Categorized Shapes (HCS), for robust 3D ear detection employing a sliding window approach and a linear Support Vector Machine (SVM) classifier. A perfect detection rate of 100% was

reported with a 0% false positive rate, on a validation set consisting of 142 range profile images from the UND, collection F, database.

d. [24] achieved an impressive recognition rate of 98.4% on the XM2VTS database. Hence, the ray transform approach by Alastair et al. outperforms Hough transform, most likely because it is more robust against disruptive factors.

e. [25] obtained 3D ear biometrics using uncalibrated video sequences. By using the shape from shading (SFS) technique, a 3D model is reconstructed on the basis of a series of video images that are registered by a variant ICP algorithm.

2.4 Morphological Operators

a. [26] addressed the problem of a fully automated ear segmentation scheme by employing morphological operators which used a low computational cost appearance-based features for segmentation, and a learning-based Bayesian classifier for determining whether the output of the segmentation is correct or not. The experiment fetched a 90% accuracy on 3750 facial images corresponding to 376 subjects in the WVU database.

b. [27] proposed a well-known distance measure termed as Modified Hausdorff Distance (MHD) for automated ear detection to decrease the effect of outliers and allowing more suitability for detection of ear in the side face images. MHD uses coordinate pairs of edge pixels derived from ear template and skin regions of the side face image to locate the ear portion.

2.5 Hybrid

a. [28] narrowed the number of possible ear candidates by detecting the skin region first before the helix template matching is applied on the curvature lines. By fusing color and curvature information, the detection rate was raised to 99.3% on the UCR dataset and 87.71% on UND collection F and a subset of collection G.

b. [29] developed an ear detection method which fused range images and corresponding 2D color images. The algorithm started by locating the concha and then used active contours for determining the ear's outer boundary. The concha serves as the reference point for placing the starting shape of the active contour model. Even though the concha is easy to localize in profile images, it may be occluded if the head pose changes or if a subject is wearing a hearing aid or ear phones. In the experiments, only ear images with minor occlusions were used where the concha is visible hence it could neither be proved nor disproved whether the approach is capable of reliably detecting ears if the concha is occluded.

c. [30] introduced the notion of "jet space similarity" for ear detection which denotes the similarity between Gabor jets and reconstructed jets obtained via Principal Component Analysis (PCA). XM2VTS database was employed for evaluation but no report the algorithm's accuracy was given.

d. [31] proposed another example for ear detection using contour lines of the ear. They located the outer contour of the ear by searching for the longest connected edge in the edge image. By selecting the top, bottom, and left points of the detected boundary, a triangle was formed with the selected points. Further, the center of the triangle was calculated and selected as reference point for image alignment.

e. [32] used skin color and template-based technique for automatic ear detection in a side profile face image. The technique first separated skin regions from non-skin regions and then searched for the ear within the skin regions using a template matching approach. Finally, the ear region was validated using a moment-based shape descriptor. Experimentation was done on an assembled database of 150 side profile face images, and yielded 94% accuracy.

f. [33] determined ear candidates by localizing arc-shaped edges in an edge image. Subsequently the arc-shaped ear candidates were verified using an Adaboost classifier. A detection rate of 100% was reported on a dataset, which consists of 376 images from 94 subjects.

g. [34] used the image ray transform, based upon an analogy to light rays, to detect ears in an image. This transformation is capable of highlighting tubular structures such as the

helix of the ear and spectacle frames. By exploiting the elliptical shape of the helix, this method was used to segment the ear region. This technique achieved a detection rate of 99.6% using the XM2VTS database.

h.   [35] extracted ears from 2D images using edge images and active contours. The approach was evaluated on a database which consists of 100 subjects with 7 images per subject. A special imaging device was used for collecting the data ensuring constant illuminitation and camera distance for all images. Within this setting a detection rate of 94.29% was reported.

i.   [36] presented an approach on 2D ear detection using edges which combined skin segmentation and categorization of edges into convex and concave edges. Afterwards the edges in the skin region were decomposed into edge segments. These segments were composed to form an edge connectivity graph. Based on this graph the convex hull of all edges, which are believed to belong to the ear, was computed. The enclosed region was then labeled as the ear region. Prakash and Gupta proved the feasibility of edge-based ear detection on full profile images, where they achieved a detection rate of 96.63% on a subset of the UND-J2 collection.

j.   [37] proposed an approach to detect ears in facial images under uncontrolled environments with a technique named Entropic Binary Particle Swarm Optimization (EBPSO), which generated an entropy map, the highest value of which was used to localize the ear in a face image. Also, Dual Tree Complex Wavelet Transform (DTCWT) based background pruning was used to eliminate most of the background in the face image. However, this method is computationally complex so that it costs 12.18s to detect an ear on average.

2.6   Learning Based (Haar Based)

a.   [38] used AdaBoost [51] to detect the ear from a profile face as part of a multi-biometric approach for detecting drivers' profiles in a security checkpoint. In an experiment with 46 images from 23 subjects, ear detection rate of 97% was obtained with seven false positives per image.

b.   [39] used a cascaded Adaboost technique based on Haar features for ear detection. This technique is widely known in the domain of face detection as the Viola-Jones method (Viola and Jones 2004). It is a very fast and relatively robust face detection technique. The Adaboost classifier was used to detect the ear region, even in the presence of occlusions and degradation in image quality (e.g., due to motion blur). A 100% detection performance was reported on the cascaded detector tested against 203 profile images from the UND database, with a false detection rate of $5x10{-}6$. In a second experiment, they were able to detect 54 ears out of 104 partially occluded images from the XM2VTS database.

c.   [40] used the same technique as Islam et al (2008b) with acclaimed very good detection rate even when there were multiple subjects in the same image. Three test sets were used to compose a database of 434 images:

—166 images from the CAS-PEAL database with a False Rejection Rate (FRR) of 3.0% and a False   Acceptance Rate (FAR) of 3.6%;
—48 images from the UMIST database with a FRR of 2.1% and no False Acceptance;
—220 images from the USTB database with a FRR of 0.5% and FAR of 2.3%.
The main drawback of the original Viola-Jones technique is the training time, which can take several weeks in some cases.

d.   [41] presented a two-step ear detection system, which utilized arc-masking candidate extraction and AdaBoost polling verification. Firstly, the ear candidates were extracted by an arc-masking edge search algorithm; then the ear was located by rough AdaBoost polling verification.

e.   [42] applied the modified Viola-Jones technique for ear detection. The training phase of the approach is about 80 times faster than the original Viola-Jones method, and achieved approximately 95% accuracy on four different test sets (> 2000 profile images for ~ 450 persons). They presented experiments showing robust detection in the presence of partial occlusion, noise, and multiple ears at various resolutions.

f.   [43] performed an ear recognition system, in which the ear region was detected by a breed AdaBoost detector. From the detected ear region, a local feature was used to extract a region with feature-rich data points, and an ICP approach to match the ear.

2.7   Deep Learning Based

a.   [44] trained a deep CNN model named AlexNet to classify the 1.2 million images in the ImageNet Large Scale Visual Recognition Competition 2010 (LSVRC-2010) contest into 1000 different classes. The neural network consists of five convolutional layers (some layers are followed by max-polling layers) and three fully-connected layers with a final 1000-way softmax layer. They employed a regularization method named 'dropout' to reduce over-fitting and accelerate convergence. They achieved top-1 and top-5 error rates of 37.5% and 17.0% on the test data.

b.   [45] put forward a VGGNet deep model (Visual Geometry Group, Department of Engineering Science, University of Oxford.) to investigate the effect of the convolutional network depth on its accuracy of image classification. It showed that a significant improvement was achieved by pushing the depth to 16–19 weight layers. The top-1 and top-5 classification error rates of 23.7% and 6.8% were reported on ImageNet LSVRC-2014.

c.   [46] proposed an innovative deep CNN architecture code named Inception. They designed a 22 layer deep network called GoogLeNet, the quality of which was assessed in the contest of ImageNet LSVRC-2014, and the top-5 classification error rate was 6.67%. Researchers found that the network depth was of crucial importance, and the leading results on the challenging of ImageNet dataset all exploited deep models. It has problem of degradation in the very deep network,

d.   [47] trained a 152 layer deep CNN called ResNet to solve the problem of degradation in the very deep network. Instead of learning unreferenced functions, they reformulated the layers as learning residual functions with reference to the layer inputs. These new networks were easier to optimize and achieved top-5 classification error rates of 3.57%.

e.   [48] proposed a new framework of object detection called Regions with CNN features (R-CNN). Firstly, around 2000 bottom-up region proposals were extracts from an input image. Then the features of each proposal were extracted based on a large convolutional neural network. Finally, the class-specific linear Support Vector Machines (SVMs) were used to classify each region. The R-CNN approach achieved a mean average precision (MaP) of 53.7% on PASCAL VOC 2010. However, because it performs a ConvNet for each object proposal, the time spent on computing region proposals and features (13s/image on a Graphics Processing Unit (GPU) or 53s/image on a CPU) cannot be ignored for an object detection system.

f.   [49] proposed Fast R-CNN to speed up R-CNN by sharing computation. The network processed all the images with a CNN to produce a convalolution feature map. Then a fixed-length feature vector was extracted from the feature map for each object proposal. Each feature vector was fed into fully connected layers and output the bounding-box of each object. Fast R-CNN processed images were 213 times faster than R-CNN and achieved a 65.7% MaP on PASCAL VOC 2012. Although the improved network reduced the running time of the detection networks, the computation of exposing the region proposal was a bottleneck. Fast R-CNN was faster than R-CNN because the convolutional operation was done only once per image and a feature map was generated from it. It also used selective search to find the region proposals hence, slow and time-consuming.

g.   [50] proposed a modified network called Faster R-CNN which was able to eliminate the selective search algorithm by using a separate network and lets the network learn the region proposals therefore can be used for real-time object detection. In this work, a Region Proposal Network (RPN) was introduced which shared the full-image convolutional features with the detection network, enabling nearly cost-free region proposals. The RPN and Fast R-CNN were trained to share convolutional features with an alternating optimization. The detection system has a frame rate of 5 fps on a GPU,

while achieving 70.4% MaP on PASCAL VOC 2012. Schemes based on Faster R-CNN have obtained impressive performances on object detection in images captured from real world situations, but the extent of biometric application using Faster R-CNN algorithm has not been reported so far. On the other hand, Faster R-CNN may fail to distinguish the correct human ear from ear shape objects without the information of ear location context and also generated a lot of false positives in a real world application.

h. [51] proposed an efficient technique involving Multiple Scale Faster Region-based Convolutional Neural Networks (Faster R-CNN) to detect ears from 2D profile images in natural images automatically. Firstly, three regions of different scales were detected to infer the information about the ear location context within the image. Then an ear region filtering approach is proposed to extract the correct ear region and eliminate the false positives automatically. In an experiment with a test set of 200 web images (with variable photographic conditions), 98% of ears were accurately detected. Experiments were likewise conducted on UND-J2 and UBEAR dataset, which contain large occlusion, scale, and pose variations. Detection rates of 100% and 98.22%, respectively, demonstrate the effectiveness of the proposed approach.

i. [52] evaluated the use of Convolutional Neural Networks (CNNs) together with Geometric Morphormetrics (GM) for automatic ear detection in the presence of partial occlusions and a Covex Hull Algorithm for ear area segmentation. The CVL dataset was used.

j. [53] presented Faster Region CNN as ear localizer model to segment ear. The model was evaluated on two wild databases and the results signified that the model is invariant to environmental condition.

3. COMPARISON OF EAR DETECTION METHODS AND THEIR ACCURACIES

Table 1 gives a summary of major algorithms reviewed in this paper based on the fundamental algorithm employed, author(s), detection performance/ accuracy level and ear database that was used for validation.

Technique	Authors/Publications	Detection Method	Type	Database	Perf (%)	Limitation
Computer Assisted.	[6]	Two-line landmark	2D 2D	UND-f NA	84.1	Not robust to pose variation &hair covering
	[7]	Modified snake algorithm and ovoid model	2D	IIT Delhi	98	
	[9]	Snake Model	2D	USTD	97.2	
	[8]	Landmark Detector	3D	IIT Delhi UND-J2	95.2 78.8	
	[10]	Pit Detection +Active Contour	3D	UND	85.5	Not robust to pose variation &hair covering
	[11]	Active Contour Model	2D	NA	76.43	High computational time
Template Matching	[12]	Gaussian pyramid Hierarchical Pyramid	2D	NA	NA	
	[13]	Histogram of Shape Index Canny Edge-Detector Based	3D	NA UCR	100 91.5	
	[14]	Edge Orientation Pattern	2D	USTB II	93.34	Does not work under realistic condition
	[15]	Edge Detection Based Skin segmentation	2D	IITK	100	
	[16]	Edge Connectivity Graph	2D	NA	80	Not robust to background noise or hair covering around ear
	[17]	Adaptive Histogram	2D	CVL	70	
	[18]		3D	CVL	99.38	
	[19]	Predefined binary ear template				Work only when the template was defined to cope with changes
	[20]		2D	NA	96.2	

	Ref	Method	2D/3D	Database	Result	Remark
Shape Based	[21]	Step Edge Magnitude	3D	UCR	92.6	Can only work on profile image
	[22]	Hough Transform	2D	XM2VTS UND-F	100 91	
	[23]	Histograms of Categorized Shapes (HCS) Ray Transform	3D	UND-F	100	
	[24]	Shape from Shading (SFS)	2D	XMSVTS	98.4	
	[25]		3D	UND	95	
Morphological Operators	[26]	Low computational Cost appearance-based features	2D	WVU	90	
	[27]	Modified Hausdorff Distance Based (MHD)	2D	USTD-I IITD	98.33 99.60	
Hybrid	[28]	Shape Model and ICP	2D	UCR UND	99.3 87.71	Can only work on profile image
	[29]	Concha and Active contours Jet Space Similarity	2D	UND-F	97.6	
	[30]	Edge Detection & Line	2D	XM2VTS	NA	
	[31]	Tracing Skin color & Template base	2D	NA	98.05	Work only with small background image
	[32]	Arc Masking Extraction + Adaboost Polling Verification Image Ray Transform	2D	NA	94	Only perf better when the images include facial parts
	[33]	Edge images and Active Contours	2D	UND	100	
	[34]	Skin colour &Graph matching	2D	XM2VTS	99.6	
	[35]	Haar Cascade+Active Shape Model+Dijkstras	2D	NA	94.29	
	[36]	Shortest Path Algorithm	2D	UND	96.63	
	[37]	EBPSO and DTCWT	3D	NA	92.92	Computationally complex
Learning Based (Haar-based)	[38]	Adaboost	2D	UND	97	
	[39]	Cascaded Adaboost	2D 2D	UND XM2VTS	99.89	Training of the classifier takes several days
	[40]	Cascaded Adaboost	2D	CAS - PEAL	52	
	[41]	Improved Adaboost	2D		88.72	
	[42]	Modified Adaboost	2D	UND	95.8	
	[43]	Breed Adaboost	2D		95	Lack robustness in practice
Deep Learning Based	[44]	CNN (ALexNet)	2D			
	[45]	CNN (VGGNet)	2D			Degradation in a very deep network
	[46]	Innovative deep CNN (GoogLeNet	2D			
	[47]	CNN ResNet	2D			
	[48]	Region with CNN	2D		Map 53.7	
	[49]	Fast R-CNN	2D		MaP 65.7	
	[50]	Faster R-CNN	2D			Generate bad candidate region proposal
	[51]	Multiple Scale Faster R-CNN	3D	WebEar UNN-J2	98 100	Uses selective search which is slow and time consuming

	[53]	Faster Region Convolutional Neural Network (Faster R-CNN)	3D	UND-J2 UBEAR-II	100 95	Generate lot of False Positive
	[52]	CNNs with Geometric Morphormetrics (GM)	3D	USTB-III CVL	99.08	Fully automatic, fast, and robust against occlusion Invariant to environmental condition

TABLE 1: Summary of ear detection methods and their accuracy.

4. CONCLUSION

This review focused on the various ear detection techniques used by researchers yet, such as semi-automated technique, template matching, morphological operations, shape feature, hybrid, learning based (Haar based) and deep learning based techniques and the results. This will be helpful for the researchers to detect ear from the image and perform further operations on it.

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