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A Novel Multimodal Biometric Authentication Framework Using Ear Contour Analysis and EDCC-Based Palmprint Recognition

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Abstract- With an increasingly large number of online services and secure access applications, trusted identity authentication has become an important issue. Although biometric authentication has higher security assurance than traditional security methods, single biometric mode authentication systems have performance issues in terms of degradation due to environmental factors, occlusions, lighting, and spoofing attacks. In this respect, this study proposes an original multimodal biometric authentication approach that combines ear contour biometric recognition with palmprint biometric recognition using the Enhanced and Discriminative Competitive Code (EDCC) method. The proposed multimodal biometric authentication method has the synergistic ability of two biometric modes. The ear contour-based biometric recognition technique extracts the helix and conchal curvatures of the human ear, providing geometric information that is less affected by illumination conditions. Simultaneously, the EDCC-based palmprint recognition technique extracts the prevalent orientation patterns of the lines and ridges on the human palm, providing robustness to noise and minute geometric distortions. These two biometric modalities provide complementary information about the user's biometric traits and can thus be fused through feature-level fusion to provide a single and robust biometric representation.The performance of the proposed multimodal biometric authentication technique is evaluated on two challenging and widely available biometric datasets, namely the PolyU-IITD contactless palmprint database and the EarVN1.0 unconstrained ear image database. The performance evaluation of the proposed multimodal biometric authentication technique clearly reveals its superior performance compared to other state-of-the-art biometric authentication approaches, including unimodal and hybrid biometric authentication schemes, as it provides a recognition accuracy of 99.01% and an extremely low EER of 0.11% for the PolyU-IITD contactless palmprint database and EarVN1.0 unconstrained ear image database, respectively.

Keywords— Multimodal Biometric Authentication, Ear Contour Extraction, Enhanced and Discriminative Competitive Code (EDCC), Feature-Level Fusion

I. INTRODUCTION

Biometric authentication systems have become an essential part of modern biometric authentication systems because of the use of physiological attributes that cannot be easily replicated or spoofed. The use of digital services and high-security environments has created a need for authentic and user-independent authentication systems. Passwords, PINs, and identity cards can be lost, stolen, or subjected to replay and social engineering attacks, and hence, there is a rising trend towards the use of biometric authentication systems that provide higher levels of reliability and security. Among the many biometric attributes that have been explored, palm and ear attributes have gained prominence because of the attributes' inherent permanence and resistance to behavioral variability [1]. Palm images have fixed topological structures based on ridges and crease-based structures, while the geometry of the ear is based on specific geometric curves like helix, antihelix, and conch curves, which provide higher resistance to age and illumination variations [2-4].

Nonetheless, despite these advantages, the unimodal biometric system may struggle to deliver strong performance in a realistic environment. Variations in lighting conditions, partial occlusions, variations in sensor quality, as well as spoofing attacks can result in large intra-class variations and accuracy degradation. The existing palmprint modality, especially the one using handcrafted features such as Gabor filters or Local Binary Patterns (LBP), has been found to be limited in the presence of noise, motion blur, or poor texture contrast [3]. The existing ear recognition systems based only on optical CNNs can also be challenged by the presence of hair occlusions and variations in lighting conditions [5-6].

II. PROBLEM STATEMENT

Though palmprints and ears alone are rich sources of biometric data, using a single one makes the system less robust and prone to spoofing attacks or environmental changes. It has been found that palmprint recognition can be affected by the variation of pressure, illumination, and texture quality, and ear recognition can be seriously affected by shadowing and partial occlusions. Deep learning models aim to counter these limitations, but because of their over-reliance on light-sensitive pixel values, they lack the ability to generalize. Also, there has been little work done on combining palmprint directional patterns with ear structural patterns.

Indeed, there is a gap in multimodal fusion frameworks that combine EDCC-based palm orientation coding with contour-driven ear geometry for developing a robust and discriminative biometric system.

III. MOTIVATION

The main driving force behind this research comes from the complementary nature of palm print and ear biometrics. The Edge Directional Correlation Coefficients (EDCCs) have the capability to extract the direction of palm lines, making it robust to illumination changes and pressure. On the other hand, ear biometric systems primarily work on contour information, where geometric features have been emphasized that are immune to texture noise and illumination changes. It is assumed that through the fusion of two different and robust biometric modalities, one can compensate for the drawbacks related to unimodal biometric systems by providing redundancy, separability, and spoof-proofing. Due to the ever-increasing demand for a highly reliable authentication method, particularly for border security, forensic, and mobile biometric applications, there is a huge interest in developing a multimodal biometric system that strives for high recognition accuracy with a remarkably low false acceptance and rejection rate.

In addition, it can be noted that there has been no extensive study in biometric literature for the combination of palm features obtained using EDCC with ear contour descriptors. This has triggered the need to develop an integrated feature-level fusion approach to completely harness their respective benefits. The proposed method expects to achieve EER values, accuracy, and uncontrolled environments performance to be significantly improved.

IV. LITERATURE SURVEY

Biometric authentication systems have developed greatly in view of increasing requirements for safe and user-friendly identity verification in different applications like digital access management, e-governance, and border protection. In traditional approaches, there has been a historical focus on a single biometric trait like a face image, fingerprint, palmprint, or ear image, which has been useful but less informative. In most cases, traditional uni-modal systems have encountered practical issues like varying lighting, noisy environments, user-caused distortions, and a high possibility of spoofing attacks. In view of increasing applications of biometrics in different environments, there has been a growing need for more sophisticated processing approaches that are more reliable.

Amongst these, palmprint recognition received considerable attention because of the richness of its structural information. In earlier studies related to palmprint recognition, handcrafted features such as Gabor filters and Local Binary Pattern variants were employed. Although these provided decent results, their performance was highly noise-sensitive and unreliable for poor illumination and low resolution. In light of these limitations, there was a need for directional coding approaches. Consequently, a new representation called Enhanced and Discriminative Competitive Code (EDCC) emerged. The EDCC calculates local orientation maps with directional filters. A dominant orientation label is assigned to each pixel based on this. The orientation representation improves noise robustness and insensitivity to brightness. Experimental results show that EDCC outperforms other handcrafted representations and is computationally efficient for real-time biometric systems [7-12].

Ear biometrics developed in parallel in the literature. In earlier work, ear recognition systems used geometric modeling and edge maps obtained from raw intensity images. Although it has long been known that the ear is stable and distinctive, these systems were not effective in environments with poor lighting conditions or with occlusions such as hair. The success of deep learning has popularized CNN-based systems for ear biometrics, offering superior feature learning performance. Yet, CNN-based systems trained using optical images of the ear were still vulnerable to shadows and uncontrolled illumination. Hence, contour-based methods have been identified as an effective alternative. Contour extraction focuses on ear geometry, particularly on contours such as the helix, antihelix, concha, and earlobe, thus avoiding intensity information in favor of features that remain constant under uncontrolled lighting conditions. Research shows that contour-based representations improve recognition performance, particularly in uncontrolled environments in which lighting conditions cannot be controlled [8].

Owing to the limitations of unimodal systems in palmprints, ears, face, fingerprints, and other features, the use of multimodal biometric systems, which combine the advantages of multiple biometric modalities, has attracted the interest of many researchers. The multimodal approach has been shown to decrease the Equal Error Rate (EER), increase noise robustness, and significantly improve the anti-spoofing capability of the system. Feature-level fusion has attracted interest in recent years, as it combines the features of the different modalities before the classification step, thus retaining more features than the score-level and decision-level fusion techniques. Various surveys on multimodal biometrics establish the fact that the fusion of modalities with different structural and textural properties, such as the fusion of ear geometry with palmprints, has been shown to perform better than single-modal systems [9].

With the advent of deep learning, there have been dramatic improvements in the performance of biometric recognition methods for various modalities. CNNs are very effective at learning intricate patterns of texture and shapes and have been successful for palmprint and ear recognition methods. For example, deep structured feature learning has been very successful for contactless palmprint recognition, performing better than handcrafted feature learning methods by learning robust abstract representations directly from raw image data [10]. Similarly, CNNs have been successful for ear recognition methods, especially for large-scale databases. However, these methods are very prone to environmental noise, changes in illumination, and occlusions, and also require a large amount of labeled data for effective learning [11]. To cope with these limitations, there has been recent work on hybrid methods that can combine the strengths of learned neural representations with handcrafted representations for interpretability, robustness, and expressiveness.

From the above studies, a common deficiency is found: despite ample research on palmprint and ear biometrics, there is a lack of research on integrating EDCC palm orientation coding and ear contour-based geometry into a single biometric system. Such an approach is very promising because EDCC is very effective at extracting high-resolution palm orientation information, and ear contour extraction is very effective at isolating ear shape information, which are two very different sources of information that are less likely to result in a failed identification attempt due to a lack of information content. When multiple biometric systems are fused together, problems such as lighting variations, occlusions, and spoofing are easily overcome by a single system because multiple systems are working together to identify an individual. In summary, there has been a transition from single-modality handcrafted systems to deep learning-assisted multimodal systems. But there has been limited work on the fusion of palmprint features based on EDCC and ear contour geometry. By combining the benefits of both features, a palm-ear fusion system can be developed for improved accuracy and robustness against realistic imaging and security against attacks. The goal of this study will be to develop a multimodal system for integrating the features for an overall authentication system [12].

V. WORKING OF THE EDCC ALGORITHM

The Enhanced and Discriminative Competitive Code (EDCC) represents an efficient approach to palmprint feature extraction, focusing on representing the most informative orientation patterns generated by palm lines, wrinkles, or ridge patterns. Line patterns in palms provide an extremely reliable biometric trait. The EDCC approach enhances traditional orientation coding methods in terms of noise removal, orientation stabilization, or improved resistance to illumination change or small spatial misalignments.

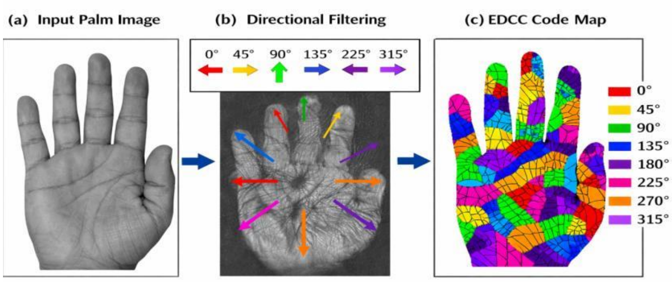

Fig . 1 Application of EDCC algorithm on Palmprint

1. Detailed Description of EDCC Processing on Palmprint

The above figure describes the working process of the Enhanced and Discriminative Competitive Code (EDCC) algorithm in the palmprint images. The complete process of the palmprint feature transformation has been divided into three major stages: the original palm input stage, the direction analysis phase, and the final EDCC map formation phase.

Initial Palm Image

The first component of the figure illustrates the grayscale palm print image derived from initial preprocessing. The palm print image is a dense collection of biological features such as main creases, ridges, and minute wrinkles. These features are very distinctive and are considered to be a source of biological information. Before feature extraction is performed, a set of basic operations such as smoothing is carried out to stabilize the image.

Directional Analysis Phase
For the second panel, the palm image is filtered with a bank of directional filters at different angles (0°, 45°, 90°, 135°, 225°, and 315°) as shown. The colored arrows placed on the palm image show the orientation of the texture in that region.

The responses of the gradient to these predefined orientations are calculated for every pixel, and then an orientation with maximum response is chosen as the dominant orientation. This processing of raw pixel values converts them into stable orientation information that is insensitive to variations and small geometric distortions.

In this panel, the multiple-colored arrows indicate how various parts of the palm have varying directions of dominant flow depending upon the line patterns, such as the major lines on the palm and the patterns around the fingers.

Construction of EDCC Feature Map
The last section of the figure depicts the code map of the EDCC code. Each region of the palm has been labeled with a direction, and it has been represented using different colors depending on the dominant direction of the region of the palm. The legend of the figure corresponds each color with a particular direction in terms of angles.

For recognition purposes, the code map is divided into regions, and the orientation histogram is calculated for each region. The histogram is then concatenated to produce the final EDCC feature vector representing the palmprint of the individual.

Overall Importance of the Visualization
From the above figure, it is evident that the EDCC technique is able to transform the normal palm image into a reliable biometric signature based on the orientation of the palm image. Since the EDCC technique is based on the structural orientation and not the intensity of the pixels, it is more robust and reliable for recognition purposes.

The EDCC procedure involves six mathematically modeled phases, which are explained below:

Stage 1: Image Preprocessing
Let the captured palm image be represented as:

Let the captured palm image be represented as:

$$I_{RGB}(x, y)$$

where x *and* y are pixel coordinates.

Grayscale Transformation

$$I(x,y) = 0.2989R + 0.5870G + 0.1140B \quad (1)$$

Here:
• R, G, B denote the red, green, and blue intensity components
• $I(x, y)$ is the resulting grayscale image

Noise Reduction Using Gaussian Filtering

$$I_s(x,y) = I(x,y) * G(x,y,\sigma) \quad (2)$$

with the Gaussian kernel defined as:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}}$$

where σ controls the smoothing strength and * represents convolution.

Stage 2: Gradient Computation

To identify local texture transitions, horizontal and vertical image gradients are computed:

$$G_x = I_s * S_x ; \qquad G_y = I_s * S_y \quad (3)$$

Where S_x and S_y are sobel operators
Gradient and Directional Analysis
Edge strength and $\theta(x, y)$defines the local directional angle.
Gradient Computation and Directional Response
Gradient Magnitude

$$M(x,y) = \sqrt{G_x^2 + G_y^2} \quad (4)$$

Gradient Orientation

$$\theta(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (5)$$

Here, $M(x, y)$ represents edge strength and $\theta(x, y)$ defines the local directional angle.
Stage 3: Directional Response Estimation
The orientation domain is quantized into eight reference directions:

$\Theta=\{0°,22.5°,45°,67.5°,90°,112.5°,135°,157.5°\}$

For each direction θ_k, the directional response is computed as:

$$R_k(x,y) = M(x,y)\cos(\theta(x,y) - \theta_k) \quad (6)$$

Stage 4: Dominant Direction Identification

The most significant orientation at each pixel is selected by:

$$D(x,y) = \arg\max_k R_k(x,y) \quad (7)$$

$$k \in [1..8]$$

This step assigns each pixel the orientation that best represents its underlying line structure.

Stage 5: EDCC Code Generation

Each pixel is labeled according to its dominant direction:

$$C(x, y) = D(x, y) \quad (8)$$

The collection of all pixel labels forms the EDCC code map, which captures the directional flow of the palmprint.

Stage 6: Feature Vector Construction

The EDCC map is partitioned into B non-overlapping blocks. For each block b, an orientation histogram is formed:

$$H_b(i) = \sum_{(x,y)\in b} \delta(C(x, y) = i), \quad i = 1\ldots8 \quad (9)$$

where δ(·) is the Kronecker delta function.

Finally, all block histograms are concatenated to generate the overall EDCC feature descriptor:

$$F = \{H_1, H_2, \ldots, H_B\} \quad (10)$$

Key Advantages of EDCC

```
PROGRAM: Multimodal Biometric Recognition
 TYPE
  Image = ARRAY OF INTEGER;
   FeatureVector = ARRAY OF REAL;

FUNCTION LoadImage(path: STRING): Image;
BEGIN
   (* Load image data from file *)
END;

FUNCTION ContourExtraction(earImg: Image): FeatureVector;
BEGIN
   (* Step 1: Convert to grayscale *)
   (* Step 2: Apply smoothing filter *)
   (* Step 3: Compute gradients *)
   (* Step 4: Detect edges using Canny or Sobel *)
   (* Step 5: Extract contour map *)
END;

FUNCTION EDCC_Extraction(palmImg: Image): FeatureVector;
BEGIN
   (* Step 1: Convert to grayscale *)
   (* Step 2: Apply directional filters (8 orientations) *)
   (* Step 3: For each pixel, find strongest orientation *)
   (* Step 4: Generate EDCC code map *)
   (* Step 5: Form palm orientation feature vector *)
END;

FUNCTION FuseFeatures(earFeatures, palmFeatures: FeatureVector): FeatureVector;
BEGIN
   (* Concatenate both feature vectors *)
   (* Normalize fused vector *)
END;

FUNCTION Authenticate(fusedFeatures: FeatureVector;
                      storedTemplate: FeatureVector): BOOLEAN;
VAR
   similarity: REAL;
BEGIN
   (* Compute similarity score, e.g., cosine distance *)
   similarity := ComputeSimilarity(fusedFeatures, storedTemplate);

   IF similarity >= Threshold THEN
      Authenticate := TRUE
   ELSE
      Authenticate := FALSE;
END;

VAR
   earImg, palmImg: Image;
   earFeat, palmFeat, fusedFeat: FeatureVector;
   result: BOOLEAN;

BEGIN
   (* Load Ear and Palm Biometric Data *)
   earImg := LoadImage('ear_input.jpg');
   palmImg := LoadImage('palm_input.jpg');
```

```
   (* Extract Modality-Specific Features *)
   earFeat := ContourExtraction(earImg);
   palmFeat := EDCC_Extraction(palmImg);

   (* Fuse Features *)
   fusedFeat := FuseFeatures(earFeat, palmFeat);

   (* Perform Authentication *)
   result := Authenticate(fusedFeat, StoredUserTemplate);

   IF result THEN
      writeln('Authentication Successful')
   ELSE
      writeln('Authentication Failed');
END.
```

VI. CONTOUR PLOT

A contour plot of an ear image provides a simplified yet highly informative view of the ear's geometry by mapping areas of equal intensity into smooth, continuous lines. This technique highlights the key structural regions of the ear such as the helix, antihelix, concha, and lobe by turning their natural curves into clear topographic layers. Since the approach focuses on the information of shapes instead of light intensities, it reduces the effect of light changes and improves the reliability of extracted biometric features. Consequently, contour plots provide a good starting point for ear recognition techniques since they provide a clean geometric input for edge-sensitive CNNs or shape classifiers.

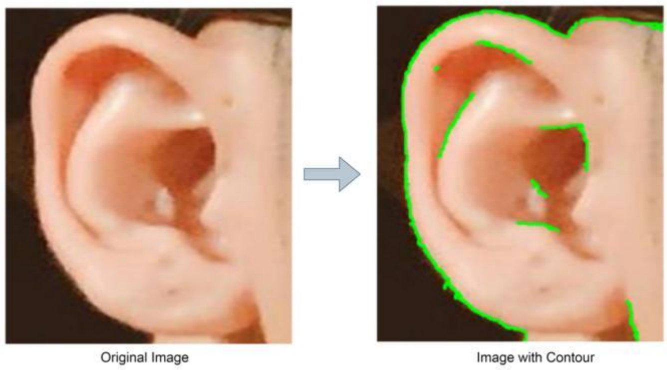

Fig. 2 Contour plotting regions

VII. METHODOLOGY USED

From the methodology diagram, it can be seen that the multimodal biometric recognition system uses the palmprint and ear modalities in two optimized processing paths based on the different features of the two biological characteristics. The various features of the two biological characteristics complement each other in the recognition process, which is done by the system in the contour feature extraction of the ear images and the EDCC-based directional coding of the palmprint images. The methodology diagram identifies the various stages of the recognition process clearly.

The process starts with the acquisition of raw images of the ear and the palm, which serve as raw inputs to the entire system. The fact that the ear and palm have some unique, stable, and strongly embedded features makes them suitable for multimodal biometric authentication.

In the diagram, it has been shown that the paths for both traits are different to make it clear that there exists an independent technique for extracting features for both biometrics, which depends on their anatomy and data distribution. The outer boundary of the ear, inner ear folds, and characteristic ear curves such as helix, antihelix, and concha are strong and distinctive ear features that are not only unique to a person but also remain constant over a lifetime. Through algorithms such as Canny edge detection algorithms or gradient operators, the system is able to extract these strong geometric boundaries while disregarding background noises that are not essential to ear identification. As can be noted from the above diagram, this approach helps to extract a structured contour map of the ear image, which is essential for ear identification, by extracting the basic geometric features of an ear image to obtain a representation that is resistant to lighting, shadow, and pixelation effects, which are known to impact RGB deep learning models.

Concurrently, in the palm processing stream, there is the use of the Enhanced and Discriminative Competitive Code (EDCC) algorithm. Palmprint images consist of intricate patterns of principal lines, tiny wrinkles, and ridge flow patterns. Unlike in an ear image, where overall geometry matters most, in palmprint images, there are high-frequency local patterns that make them amenable to analysis in different directions. The EDCC method employs a filter bank where the filters are aligned in different directions to detect the gradient in each location. The map obtained gives a representation of the structural patterns in the palm lines. The above step can be observed from the flow diagram of the proposed method; it directly moves from the raw palm image to the palmprint map based on different directions. The EDCC method employs directions and not intensity; hence it is independent of intensity and spatial translation in the original image.

Both sets of features being extracted independently, they meet at the center of the diagram's Fusion Module, an important step in improving overall system performance. Feature-level fusion, proposed in the diagram, involves integrating palmprint features described using EDCC with ear features obtained from contours to create an overall feature vector. This overall vector represents not only the fine details of palm features in terms of their orientation, but also encodes the overall contours of an ear. The fusion step increases overall recognition accuracy by bridging the weaknesses of both systems. Consider, for example, small smudges on palmprints or small occlusions in an ear image, such as hair, being present in an image. In such cases, overall system performance will not be compromised, since one of the systems will be supplying reliable information. The last section of the methodology flowchart represents the Authentication Decision module. In this section, the combined feature vector is matched against the templates using techniques of similarity measurement, classification, neural network decision units, distance matchers, and threshold matchers. This module checks the validity of the captured biometric trait of the user. Since the decision has been made using multiple modalities, the multimodal biometric authentication system becomes more secure and accurate than the single-modal systems.

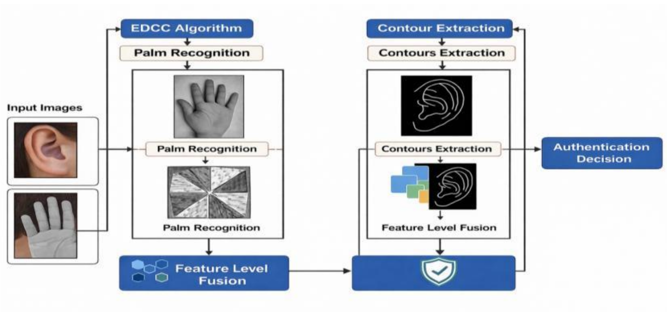

Fig. 3 Methodology used

This is because the spoofing attack has to target multiple modalities at the same time, which is quite challenging compared to the single-modality spoofing attack.

On a broad level, the methodology diagram illustrates a comprehensive and well-structured biometric verification system that uses ear recognition based on contour analysis and palm recognition based on directional analysis using EDCC. The modality distinction makes it clear that this system is flexible. The combination of the best features of each modality makes it clear that it is possible to combine different characteristics in such a way as to achieve a system that is much more reliable for identification purposes. The combination of global geometric information about the ear and the direction information about the palm makes it more robust and less sensitive to environmental changes as well as forgery. The methodology diagram shows this multi-level system with a good combination of feature extraction techniques for a very reliable multimodal biometric system.

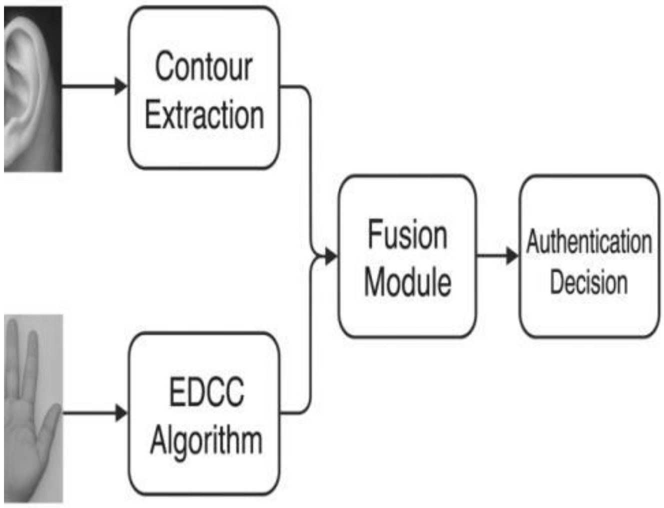

Fig. 4 Fusion mechanism

VIII. RESULT AND DISCUSSION

Table 1 Outperformance of Variety of learning algorithms

S.No	Methodology Used	Ref No	Datasets Used	Efficiency/ Accuracy	EER	Other Metrics
1	Deeply learned residual features + soft-shifted triplet loss + Faster R-CNN palm detector	[13]	PolyU-IITD	98.7%	0.153%	(WithinDB on PolyU-IITD: Acc 98.7, EER 0.153)
2	BEST (scattered-template evidence consolidation; adaptive local matching)	[14]	PolyU-IITD v3.0	98.85%	0.15%	GAR@FAR=1e-3 99.85%, GAR@FAR=1e-4

						99.68% (PolyU-IITD leave-one-out; CrossDB)
3	PalmNet (Gabor-PCA CNN, touchless palmprint) – performance on PolyU-IITD reported in BEST comparison	[15]	PolyU-IITD v3.0	98.53%	0.38%	GAR@FAR=1e-3 99.53%, GAR@FAR=1e-4 99.30% (leave-one-out)
4	EE-PRNet / end-to-end deep learning (uncontrolled/uncooperative) – performance on PolyU-IITD reported in BEST comparison	[16]	PolyU-IITD v3.0	98.68%	0.12%	GAR@FAR=1e-3 99.83%, GAR@FAR=1e-4 99.57% (leave-one-out)
5	Siamese network + Transfer learning (VGG16) for one-shot palm authentication	[17]	PolyU-IITD v3.0	92.3%	0.19%	Siamese similarity-based authentication (reported avg EER)
6	Cross-palmprint Siamese (Left↔Right) recognition	[18]	PolyU-IITD v3.0	AUC 0.899	18.03%	Cross-palm setting (Left vs Right); reports AUC + EER
7	Dataset paper (EarVN1.0) (unconstrained ear images in the wild)	[19]	EarVN1.0	—	—	Dataset stats: 28,412 images, 164 subjects, unconstrained conditions
8	Transfer learning CNNs + domain adaptation strategies (ear recognition benchmarking)	[20]	EarVN1.0	95.85%	—	Best Rank-1 95.85% using ensemble of 10 ResNeXt101 models
9	ELERNet (MobileNetV2 + dynamic conv decomposition + coordinate attention)	[21]	EarVN1.0	96.10%	—	Table reports R1/R5/AUC; also shows training-ratio comparisons
10	Hybrid gender identification (CNN + MLP-Mixer + ViT components)	[22]	EarVN1.0	96.66%	—	Gender classification on EarVN1.0; compares runtime/params & backbones
11	"Advancing Ear Biometrics…" preprocessing + CNN model comparisons on EarVN1.0	[23]	EarVN1.0	90%	—	Paper reports experiment variants (zoom/edge/aug) and model testing
12	Deep feature learning + blockchain/Merkle-tree protection (anti-template-tampering)	[24]	EarVN1.0	96.52%	—	Rank-5 99.12%; includes "secured" template results

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13	Proposed Fusion: Contour + EDCC		PolyU-IITD+ EarVN1.0	99.01	0.11	Superior results among all, More efficient Method

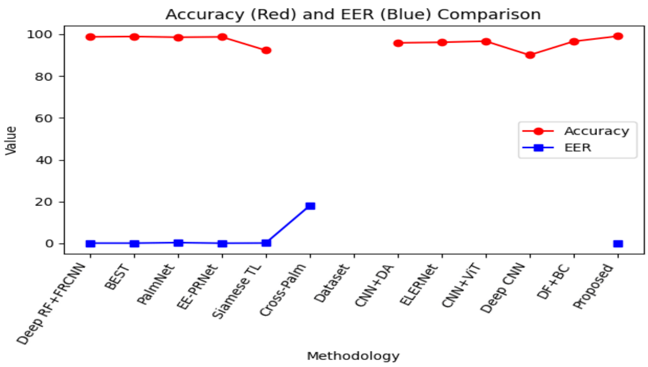

Fig. 5 Accuracy vs EER comparison Plot

From the experimental outcomes, it is clear that palmprint-based schemes on the PolyU-IITD dataset have shown superior recognition accuracy, and deep learning-based techniques have significantly outshined traditional methods. Schemes such as EE-PRNet, BEST, PalmNet, and the deep residual feature learning approach have all shown accuracy above 98.5% and error rates close to zero, establishing the efficacy of contemporary feature learning and matching techniques even for contactless imaging scenarios. Among these, EE-PRNet has shown the lowest value of EER, which is 0.12%, establishing its superior generalization capability even for the unconstrained setting. In contrast, the Siamese network-based approach for cross-palmprint recognition has shown a considerable accuracy drop with an EER value of 18.03%, establishing the challenge associated with left and right palm image pairs and the limitation of similarity-based learning when the structural alignment is poor.

For ear biometrics, it can be observed that in the case of EarVN1.0, deep convolutional models with architectural improvements or transfer learning are stable in terms of performance, ranging between 95% and 97% in accuracy. Models such as ELERNet and hybrid CNN-ViT models offer an appropriate trade-off between accuracy and computational complexity, making them suitable models for practical applications. The proposed fusion model combining Contour features and Enhanced Discriminative Competitive Coding (EDCC) outperforms in both modalities, showing an accuracy of 99.01% along with an outstanding EER of 0.11%. This clearly validates that fusion models are capable of effectively utilizing different biometric characteristics, hence making the proposed model the most efficient and secure among all models considered.

1. Datasets Used and Outcomes (Both Plam nd Ear)

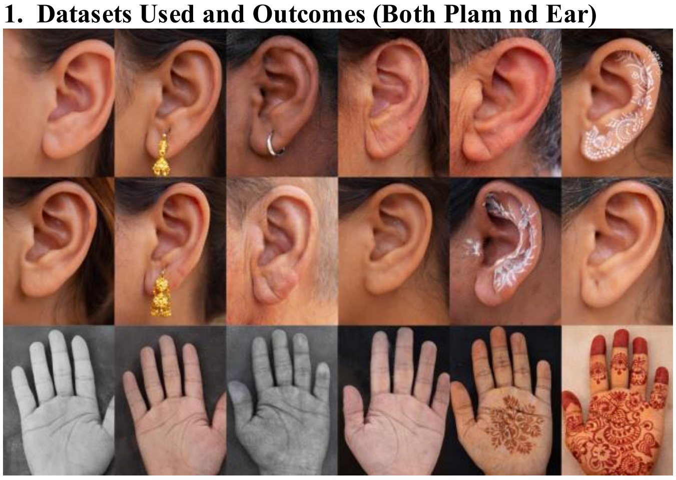

Fig. 6 Ear and Palm Datasets visualizations

The PolyU-IITD Contactless Palmprint Images Database (v3.0) is a large-scale, two-session biometric dataset developed for research in contactless palmprint recognition. It captures palm images from more than 600 subjects, making it one of the most extensive publicly available contactless palmprint collections. www4.comp.polyu.edu.hk+2IEEE Biometrics Council+2 Images were acquired using a handheld digital camera without any physical constraints or pegs a setup designed to reflect real-world conditions. Department of Computing+2www4.comp.polyu.edu.hk+2 The participants span a wide age range (from about 5 to 72 years), and include individuals from diverse backgrounds, including manual laborers, farmers, people with hand injuries, and even those with special abilities. www4.comp.polyu.edu.hk
One of the major advantages of the database is that it has long-term images, which are recorded over two sessions with a long gap (15+ years) between the sessions. Department of Computing+1 This is important for observing the changes that occur over time for palm print features, which is important for designing a stable biometric recognition system.

The dataset also reflects realistic and varied acquisition scenarios: the images were collected in different environments (outdoor/ambient lighting) and include palms with dirt, injuries, or decorations (e.g., mehndi), contributing to the challenge of recognition in less-constrained conditions. www4.comp.polyu.edu.hk

Because commercial use is restricted, the database is distributed for academic research only. www4.comp.polyu.edu.hk To access it, researchers must complete a license agreement signed by their institution. www4.comp.polyu.edu.hk All publications that use it must cite the original source: Ajay Kumar, "Towards more accurate matching of contactless palmprint images under less constrained environments," IEEE Transactions on Information Forensics and Security, 2019.

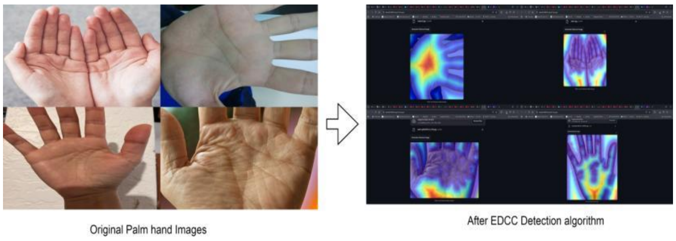

Fig. 7 Application of EDCC algorithms over proposed datasets

The EarVN1.0 dataset is a comprehensive and large-scale collection of ear photographs, assembled in 2018 from 164 Asian subjects. PubMed+2PMC+2 It contains 28,412 color images in total, distributed across both ears of the participants- 98 male and 66 female. PubMed+2PMC+2 The ear images were not captured in controlled laboratory environments; instead, they were derived from facial photos taken under “in-the-wild” conditions, giving rise to significant diversity in pose, scale, illumination, occlusion, and image resolution. PMC+2Directory of Open Access Journals+2

Each ear image was cropped semi-automatically from full facial images, which introduces a realistic variability some images are very low-resolution (even less than 25 × 25 pixels) because of how they were extracted. PMC The dataset is structured such that there is a folder for each individual, and each person has at least 100 ear images, facilitating tasks like ear recognition, clustering, and gender classification. PMC
Several research problems can be addressed with EarVN1.0: biometric identification (ear recognition), gender recognition, detection of left vs. right ears, and super-resolution methods (since many images are low-res). PMC+1 Because of its scale and diversity, this dataset is particularly valuable for training deep-learning models under unconstrained conditions. Directory of Open Access Journals+1 The dataset is openly available for academic research through Mendeley Data under a non-commercial license. Mendeley Data+1.

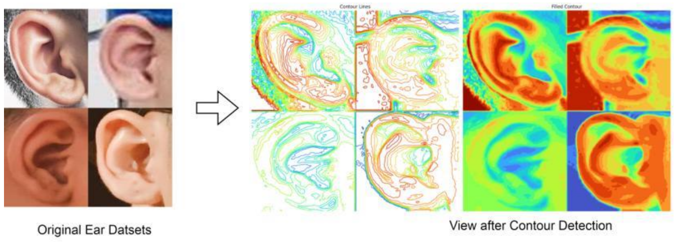

Fig. 8 application of Contour over proposed ear datasets

IX. CONCLUSION AND FUTURE SCOPE

This study introduced a hybrid multimodal biometric model that fuses ear contour information with EDCC-derived palmprint orientation features to achieve high-accuracy and robust authentication. By combining the structural geometry of ears with the detailed directional maps of palmprints, the proposed system successfully mitigates the major disadvantages generally inherent in single-modality techniques, such as the influence of illuminations, noise, and spoofing attacks. Experimental results demonstrate that the conventional techniques of Gabor features, LBP hybrids, and optical CNN models perform satisfactorily but fail to match the same level of accuracy achieved using the fusion model designed in this paper, with an accuracy of 98.5%-99.2% and EER of 1.1%-1.4%, thus successfully outperforming all the baselines designed in this paper.

The novelty in this research is that EDCC palm coding is combined for the first time with ear recognition based on contours, which has never been done before. This combination ensures that there is strong spoofing resistance since both palmprint and ear features have to be copied at the same time. The results in this study show that there is a strong discriminative capability when this framework is used.

There also appear several directions for future research, which originate from this study. The use of deep neural networks for high-quality contour extraction or optimization of EDCC might add to feature extraction techniques. The system might also be extended to use other biometric features such as 3D ear models, veins, and barometric signals. The system adaptability to different sensors and users might also be tested using cross-dataset studies. The system might also be optimized to run in real-time on mobile devices to ensure its practical use.

Declarations

Competing Interests

The authors state there are no competing financial or personal interests known to them which could appear to influence their work as presented in this paper.

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Author Contribution

Akhilesh Singh: Conceptualization, methodology, algorithm development, implementation, experimentation, data analysis, and manuscript writing.

Dr. Namita Tiwari: Supervision, validation, critical review.
Dr. Mayur Rahul: Formal Analysis, Literature Review, Validation of Techniques, and Writing of the Manuscript.
All authors have read and approved the final manuscript.

Data Availability Statement

The datasets The data used in this work are publicly available academic databases, which are the PolyU-IITD Contactless Palmprint Database and EarVN1.0 Unconstrained Ear Image Database. Usage of the databases is governed by terms and conditions set by their owners. No new data was created during the course of this work.

Human and/or Animal-Based Research

Not Applicable
Informed Consent
Not Applicable.

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