The Impact of the Warkac Method on Palmprint Recognition Robustness and Accuracy

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Abstract

Palmprint recognition is a promising biometric method due to the stability and uniqueness of its texture patterns. This study proposes the Warkac method (Wavelet-Wiener-Gabor-KPCA-Cosine), a systematic integration of image processing and feature extraction techniques to improve the robustness and accuracy of palmprint recognition systems. The process starts with wavelet decomposition and Wiener filtering for noise reduction, followed by detail weighting to enhance dominant features. Feature extraction is carried out using a $\mathbf{7 \times 5}$ *Gabor filter, with dimensionality reduction by Kernel Principal Component Analysis (KPCA). Matching is performed using cosine similarity, which efficiently distinguishes low-dimensional biometric features. Evaluations conducted on three public databases (PolyU, IITD, CASIA) with various matching and dimensionality reduction methods show that KPCA–Cosine delivers the best performance, achieving a verification rate of 99.455% and EER of 0.00546, followed closely by LDA–Cosine. Hausdorff and Ndistance methods perform poorly, with verification rates below 55%. This study demonstrates that the proper integration of filtering and non-linear transformation techniques can significantly enhance palmprint recognition performance under diverse input conditions.*

Keywords*: palmprint recognition; image enhancement; Gabor filter; KPCA; cosine similarity*

1. Introduction

Palmprint recognition has emerged as one of the most promising biometric modalities in identification and verification systems due to its unique, stable, and forgery-resistant characteristics. These advantages position palmprint technology as a primary option in modern biometric authentication systems [1]. With the increasing demand for security, the integration of deep learning and advanced image processing techniques has become a central focus in recent biometric research [2].

Despite ongoing advancements, palmprint recognition systems still face several technical challenges. Poor image quality caused by variations in lighting, hand rotation, or motion can significantly reduce system accuracy. Moreover, the presence of noise often disrupts the feature extraction process, and conventional techniques such as PCA or histogram transformations are sometimes insufficient to capture the complexity of palmprint patterns [3]. Therefore, there is a need for new strategies that not only enhance feature sharpness but also maintain computational efficiency and robustness against input variability.

To address these issues, this study proposes the WARKAC method (Wavelet-Wiener-Gabor-KPCA-Cosine), which integrates multiple stages of image processing and feature analysis into a unified framework. The method begins with wavelet decomposition to separate the image into frequency components, followed by Wiener filtering to reduce noise and adaptive detail weighting to enhance important texture regions. Local features are then extracted using a 7×5 scale-orientation configuration of Gabor filters, which has proven effective in capturing palmprint texture patterns [2]. The resulting feature vectors are subsequently reduced in dimensionality using Kernel Principal Component Analysis (KPCA) [4], and the final matching is performed using cosine similarity, which offers high efficiency in biometric classification tasks [5].

The main objective of this research is to develop a more accurate and robust palmprint recognition method that can handle image noise, hand rotation, and various lighting conditions by utilizing a sequential integration of advanced filtering and feature extraction techniques, referred to as the WARKAC method.

The novelty of this approach lies in the comprehensive integration of these stages into a single, cohesive system. This unified pipeline has not been widely explored in previous studies, and experimental results across multiple datasets demonstrate promising performance in terms of both accuracy and robustness.

The main advantage of this method compared to conventional approaches such as PCA or histogram equalization lies in its ability to handle nonlinear variations in image data while preserving discriminative features through KPCA, and enhancing matching accuracy via cosine similarity, which is proven to be more stable against intensity variations.

The remainder of this paper is organized as follows: Section 2 presents a literature review of related works in palmprint recognition; Section 3 describes the proposed WARKAC methodology; Section 4 discusses the experimental results and performance analysis; and Section 5 concludes the study and outlines directions for future research.

2. Literatur Review

Palmprint recognition, a biometric technique that leverages the unique and stable patterns present on the human palm, has emerged as a reliable method for personal identification and authentication. It finds applications in various sectors including access control, forensics, and secure financial transactions [6]. The effectiveness of palmprint recognition systems is highly dependent on their ability to accurately extract and match palmprint features, especially in the presence of challenges such as variations in illumination, pose, and image quality. Feature extraction methods encompass both global and local approaches [7]. Global methods, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), aim to reduce dimensionality by capturing overall image characteristics [8], while local techniques, including Gabor filters and Local Binary Patterns (LBP), focus on fine-grained textural details such as ridges, wrinkles, and minutiae [9]. Effective feature extraction is a critical factor in determining the overall system performance [10].

To enhance robustness and accuracy, researchers have proposed various preprocessing methods designed to mitigate the impact of noise and distortions. This is particularly relevant in touchless palmprint recognition systems, where hand posture, illumination variability, and sensor distance introduce additional complexities. Image enhancement techniques such as histogram equalization and contrast stretching improve feature visibility, while noise reduction approaches like median and Gaussian filtering help preserve essential details. Furthermore, image stitching can be applied to construct complete palmprints from partial scans, proving especially useful in forensic scenarios [11]. The integration of advanced preprocessing and feature extraction techniques has led to the development of more resilient recognition systems [12].

The proposed Warkac method incorporates a sequence of sophisticated image processing and feature extraction steps aimed at improving palmprint recognition performance. The

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method begins with wavelet decomposition, which separates the image into distinct frequency bands to enable multi-resolution analysis [13]. This is followed by Wiener filtering to reduce noise and blurring, thereby enhancing the clarity of feature regions. Adaptive detail weighting further emphasizes significant texture components. A 7×5 Gabor filter bank is then applied to extract local textural features that are highly discriminative for palmprint patterns [14, 15]. The resulting high-dimensional feature vectors are reduced using Kernel PCA, a nonlinear transformation that maintains important class-separating information while lowering computational complexity. Finally, cosine similarity is utilized for biometric matching, offering robust and efficient comparison of low-dimensional features.

Additional studies have highlighted that combining feature-level methods such as BSIF, PCA, and LDA can improve discriminative capacity, enabling more precise matching using metrics like cosine Mahalanobis distance [16]. Advances in high-resolution fingerprint sensors have also driven interest in level-3 features, including pores, which offer increased security due to their resistance to spoofing [17]. Automatic fingerprint identification systems are gaining traction, supported by innovations in image acquisition and anti-spoofing mechanisms [18]. Techniques such as photoacoustic tomography are being explored to address limitations in data quality [19], while the need to secure biometric data remains a major consideration [20, 21.

Moreover, architectural innovations have improved contactless fingerprint acquisition [22], addressing challenges such as low ridge-valley contrast and distortion in 3D-to-2D mapping. Algorithms tailored to touchless systems are actively being developed [23]. There is also a growing interest in multimodal biometric fusion to enhance system reliability and security. In this context, it becomes increasingly imperative to evaluate the effectiveness and accuracy of palmprint recognition systems within both controlled and unconstrained environments.

3. Methodology

This research adopts a quantitative experimental approach, involving sequential biometric image processing of palmprints using the Warkac method. As illustrated in Figure 1, the stages in this method are designed to enhance the robustness and accuracy of palmprint recognition systems under various conditions, including changes in illumination, rotation, noise, and low image quality. The proposed framework consists of five main stages: (1) image acquisition and normalization, (2) image enhancement using wavelet decomposition and Wiener filtering, (3) feature extraction using 7×5 Gabor filters, (4) dimensionality reduction using Kernel PCA, and (5) matching using cosine similarity.

3.1. Image Acquisition and Normalization

The initial step in the palmprint recognition system involves acquiring images from well-established and validated public datasets, namely PolyU, IITD-India, and CASIA. These datasets are selected due to their variability in image resolution, hand orientation, and lighting conditions, thus providing a comprehensive evaluation of the generalizability of the proposed system.

Each image from the datasets is first converted into grayscale format. This conversion aims to reduce the color information that is irrelevant for texture analysis while preserving critical textural features inherent in palmprints. Grayscale representation also allows for more efficient processing, particularly in the filtering and feature extraction stages that focus on intensity values.

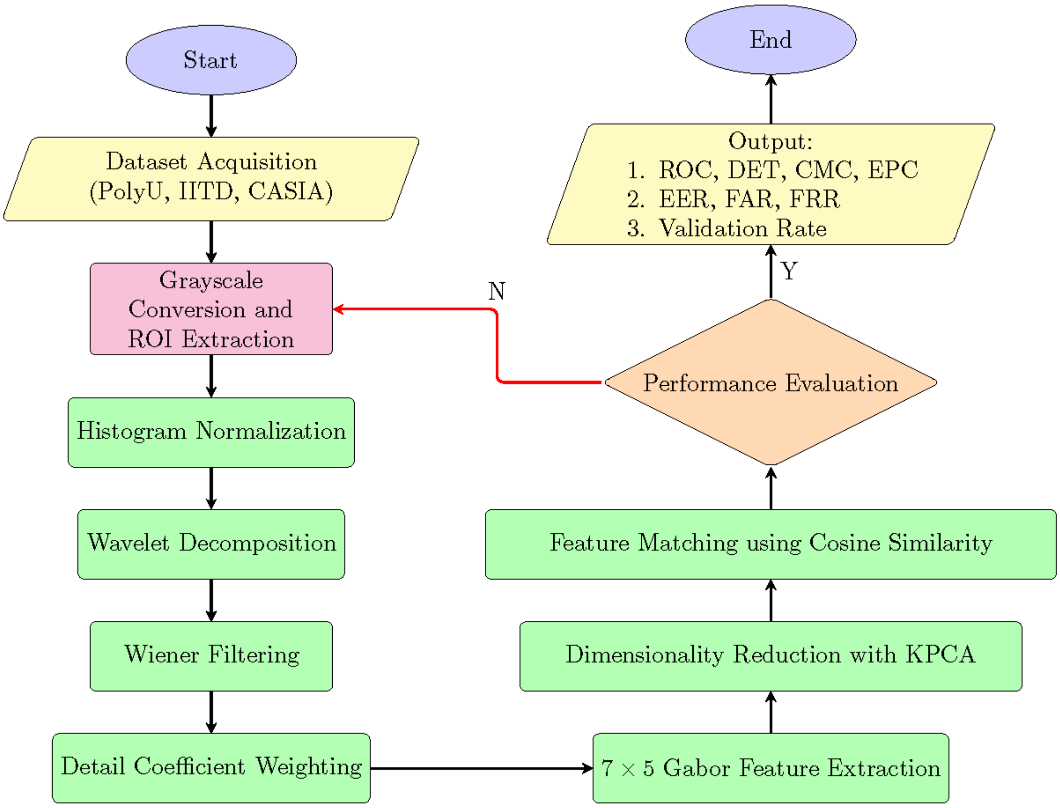

Figure 1. Illustrates the workflow of the Warkac method for palmprint recognition.

The next step is the segmentation of the Region of Interest (ROI). The ROI is determined based on hand geometry by detecting reference points such as the valley between the thumb and index finger and the base of the palm. The ROI is then systematically cropped so that only the palm area containing significant biometric information is analyzed.

To ensure intensity consistency across different images, histogram normalization is applied to each ROI. This process is crucial in mitigating uneven lighting effects and contrast variability. The intensity normalization is mathematically defined in the following equation, which maps the pixel intensity $I(x, y)$ to the full dynamic range (0–255):

$$I_n(x, y) = \frac{I(x, y) - I_{min}}{I_{max} - I_{min}} \times 255 \tag{1}$$

In this equation, I_min and I_max represent the minimum and maximum pixel intensity values in the original ROI image. This normalization process produces a more uniform intensity distribution and enhances local contrast, thereby improving the effectiveness of subsequent filtering and feature extraction stages.

3.2. Image Enhancement

Once the ROI images have been acquired and normalized, the next step is to enhance image quality to strengthen the textural features to be extracted. This enhancement process is essential to ensure system robustness against noise, low contrast, and structural artifacts commonly present in biometric images.

The enhancement stage begins with a one-level wavelet decomposition using the Haar wavelet basis. This decomposition separates the image into four primary sub-bands: the approximation component $\emptyset_A$, and the horizontal ψ_H, vertical ψ_V, and diagonal ψ_D, detail components. This separation enables the system to process low- and high-frequency information independently and in a more targeted manner for different feature types.

To improve the clarity of features in the detail sub-bands, an adaptive Wiener filter is applied to each component ψ_H, ψ_V, ψ_D. The Wiener filter is well-suited for noise suppression while preserving important image contours. The filtering process is defined in Equation (2).

$$\hat{\psi}_H = \psi_H \cdot W, \quad \hat{\psi}_H = \psi_H \cdot W, \quad \hat{\psi}_D = \psi_D \cdot W, \tag{2}$$

where W represents the adaptive Wiener filter matrix constructed based on local intensity estimation and noise variance.

Following the filtering process, adaptive weighting is applied to the filtered sub-bands. This step aims to enhance dominant structural features in the palmprint while suppressing less informative elements. The adaptive weighting for each sub-band is defined in Equation (3):

$$\hat{\psi}_H = \hat{\psi}_H \cdot \vartheta, \qquad \hat{\psi}_V = \hat{\psi}_V \cdot \vartheta, \qquad \hat{\psi}_D = \hat{\psi}_D \cdot \vartheta,, \tag{3}$$

where ϑ denotes a weighting coefficient determined based on the local intensity distribution or local entropy of the respective sub-band. The output of this stage is an enhanced image, optimized for subsequent local feature extraction using Gabor filters.

3.3. Gabor 7 × 5 Feature Extraction

After the enhancement and adaptive weighting processes, the next step is to extract local texture features that are unique to the palmprint. In this study, a two-dimensional Gabor filter bank is employed with a configuration of 7 scales and 5 orientations. This setup enables the system to capture line patterns, wrinkles, and textural structures from multiple directions and spatial frequencies.

Gabor filters are highly suitable for biometric recognition due to their ability to simultaneously represent spatial and frequency information. The two-dimensional Gabor function used in this study is defined in Equation (4)

$$G(x, y) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \phi\right) \tag{4}$$

where $x' = x\cos\theta + y\sin\theta$ represents the projected coordinate along the orientation θ. The parameter λ corresponds to the wavelength of the sinusoidal carrier (spatial frequency), γ denotes the aspect ratio that controls the elongation of the filter, σ is the width of the Gaussian envelope, and ϕ is the phase offset. The 7×5 configuration of θ and λ results in a total of 35 feature responses per image, covering a comprehensive range of orientations and scales.

Each Gabor response produces a feature map, which is then concatenated into a high-dimensional feature vector. Due to the high dimensionality, a dimensionality reduction step is required to ensure computational efficiency during the matching phase without sacrificing classification accuracy.

3.4. Dimensionality Reduction using KPCA

To reduce computational complexity and eliminate redundancy in the high-dimensional feature vectors produced by Gabor filtering, this study employs Kernel Principal Component Analysis (KPCA) for dimensionality reduction. Unlike conventional PCA, which is linear in nature, KPCA implicitly maps the input data into a high-dimensional feature space using kernel functions, thereby preserving nonlinear relationships among features.

The Gaussian kernel function used to measure similarity between two feature vectors x_i and y_i is expressed in Equation (5):

$$K(x_i, x_j) = exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right) \tag{5}$$

In Equation (5), σ is the kernel parameter that controls the width of the Gaussian distribution and the sensitivity to feature distance. The resulting KPCA projection yields a compact, low-dimensional representation that retains the most discriminative information and is ready for the final matching stage using cosine similarity.

3.5. Cosine Similarity Matching

The final stage of the palmprint recognition process involves matching the extracted feature vector of a test image with that of a reference image. In this study, cosine similarity is used as the matching metric due to its robustness to scale variations and its focus on directional similarity. This makes it particularly suitable for biometric data, which often vary in intensity or amplitude but maintain consistent discriminative patterns.

Mathematically, the cosine similarity between two KPCA-projected feature vectors $\vec{A}$ and $\vec{B}$ is defined in Equation (6):

$$cos\,(\theta) = \frac{\vec{A} \cdot \vec{B}}{||\vec{A}||\,||\vec{B}||} \tag{6}$$

In this equation, the dot product $\vec{A} \cdot \vec{B}$ measures the similarity in direction, while $||\vec{A}||$ and $||\vec{B}||$ represent the Euclidean norms of the respective vectors. A cosine value close to 1 indicates high similarity between the test and reference images, while a value near 0 suggests significant dissimilarity.

By employing cosine similarity, the system achieves efficient biometric verification while maintaining high accuracy, even under variations in lighting conditions and hand positioning during acquisition.

3.6. Performance Evaluation

To assess the performance of the Warkac-based palmprint recognition system, several standard biometric evaluation metrics are used. These include Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR), and overall accuracy. EER, which corresponds to the point at which FAR equals FRR, is often considered a key indicator of system effectiveness. The evaluation is conducted in both verification (1:1) and identification (1:N) modes.

In addition to these metrics, the system is evaluated using four commonly employed biometric performance curves:

1. Receiver Operating Characteristic (ROC) – illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR), indicating the system's ability to distinguish between genuine and impostor inputs.
2. Detection Error Tradeoff (DET) – displays the trade-off between FRR and FAR on a normal deviate scale, offering clearer visualization of system error behavior.
3. Cumulative Match Characteristic (CMC) – used in identification mode to show the correct match rate within the top-k ranked candidates.

4. Expected Performance Curve (EPC) – evaluates the system's performance stability under varying environmental parameters and configuration changes.

These curves are generated based on test results using the PolyU, IITD, and CASIA datasets. The evaluation shows that the EER values achieved are consistently low, indicating a good balance between FAR and FRR. The identification success rate at rank-1 in the CMC curve exceeds 95%, confirming the system's high accuracy. The EPC analysis further demonstrates that the system maintains stable performance across typical environmental variations found in real-world biometric applications.

4. Results and Discussion

This study evaluates the performance of the palmprint recognition system using four primary dimensionality reduction methods: KFA, KPCA, LDA, and PCA, each combined with seven different matching techniques: Euclidean, CTB, Cosine, MahCos, ModEuc, Hausdorff, and Ndistance. The evaluation is based on four key performance metrics: False Rejection Rate (FRR), False Acceptance Rate (FAR), Equal Error Rate (EER), and Verification Rate (Ver), as presented in Table 1 and Figure 2.

The KPCA method consistently demonstrates superior performance. This is evident from the KPCA–Cosine combination, which yields exceptionally low FRR and FAR values (0.00545 and 0.00546, respectively), an EER of 0.00546, and the highest verification rate of 99.455%. These results highlight the strength of KPCA, a nonlinear technique capable of capturing complex feature structures that linear methods often fail to represent effectively.

LDA also performs remarkably well, particularly when paired with Cosine Similarity, achieving a verification rate of 99.435% and an EER of only 0.00546. LDA's advantage lies in its ability to maximize between-class separability, which is crucial in biometric recognition systems.

Meanwhile, the PCA method shows competitive performance. The PCA–Cosine combination achieves a verification rate of 99.000% with an EER of 0.00999. Although not as effective as KPCA or LDA, PCA remains relevant due to its lower computational cost and robustness in varied testing environments.

On the other hand, KFA tends to produce inferior results. The highest EER values are found in the KFA–MahCos (0.33669) and KFA–Hausdorff (0.49853) combinations. Although KFA–CTB achieves a fairly good verification rate (90.818%), overall, KFA appears less capable of producing strong feature separation in the dimensionality reduction domain, especially compared to kernel-based methods like KPCA.

Table 1: Matching Metrics with Verification Rate Scaled to Percentage and Block-wise Max Highlighted

RD	Matching	FRR	FAR	EER	Ver.
KFA	Euclidean	0.24	0.24074	0.24037	76.0
KFA	CTB	0.09182	0.09166	0.09174	90.818
KFA	Cosine	0.09364	0.09368	0.09366	90.636
KFA	MahCos	0.33636	0.33701	0.33669	66.364
KFA	ModEuc	0.23091	0.2307	0.2308	76.909
KFA	Hausdorff	0.50727	0.4898	0.49853	49.273
KFA	Ndistance	0.46	0.45919	0.45959	54.0
KPCA	Euclidean	0.00727	0.00728	0.00728	99.273
KPCA	CTB	0.01455	0.01457	0.01456	98.545
KPCA	Cosine	0.00545	0.00546	0.00546	99.455
KPCA	MahCos	0.00636	0.00641	0.00639	99.364
KPCA	ModEuc	0.00727	0.00728	0.00728	99.273
KPCA	Hausdorff	0.5	0.49917	0.49959	50.0

KPCA	Ndistance	0.50182	0.5021	0.50196	49.818
LDA	Euclidean	0.03545	0.03516	0.03531	96.455
LDA	CTB	0.03909	0.03898	0.03904	96.091
LDA	Cosine	0.00565	0.00546	0.00546	99.435
LDA	MahCos	0.00636	0.00638	0.00637	99.364
LDA	ModEuc	0.03545	0.03516	0.03531	96.455
LDA	Hausdorff	0.5	0.5001	0.50005	50.0
LDA	Ndistance	0.47455	0.47513	0.47484	52.545
PCA	Euclidean	0.01455	0.01465	0.0146	98.545
PCA	CTB	0.04364	0.0436	0.04362	95.636
PCA	Cosine	0.01	0.00998	0.00999	99.0
PCA	MahCos	0.01636	0.01669	0.01653	98.364
PCA	ModEuc	0.01455	0.01465	0.0146	98.545
PCA	Hausdorff	0.49909	0.49925	0.49917	50.091
PCA	Ndistance	0.49909	0.49892	0.499	50.091

A key finding of this study is the effectiveness of the Cosine Similarity matching technique across all dimensionality reduction methods. In each block (KFA, KPCA, LDA, and PCA), the cosine-based combination consistently yields the highest verification rates compared to other matching approaches. This supports the notion that cosine similarity excels in measuring the directional consistency of feature vectors, making it robust to differences in scale or intensity while preserving spatial feature structure.

Conversely, methods such as Hausdorff and Ndistance perform poorly. Across all blocks, these techniques produce EER values near 0.5 and verification rates below 55%, indicating insufficient sensitivity in distinguishing palmprint features after dimensionality reduction.

The results of these experiments carry significant implications for the design of palmprint-based biometric systems. The combination of nonlinear dimensionality reduction methods such as KPCA with cosine-based matching proves to be highly effective and is recommended for high-accuracy applications such as secure authentication or access control.

From a technical perspective, the outstanding performance of the KPCA–Cosine and LDA–Cosine combinations highlights that the success of a biometric recognition system depends not on a single component (e.g., feature extraction or segmentation) but rather on the effective synergy between dimensionality reduction and matching techniques. Therefore, a holistic approach to pipeline selection becomes critical.

Based on the evaluation results in Table 1, the KPCA–Cosine combination is concluded to be the overall best-performing method, achieving the highest verification rate of 99.455% and the lowest EER of 0.00546. A highly competitive second-best choice is LDA–Cosine, with a verification rate of 99.435%. In contrast, methods like Hausdorff and Ndistance should be avoided in biometric recognition systems due to their lack of stability and poor performance.

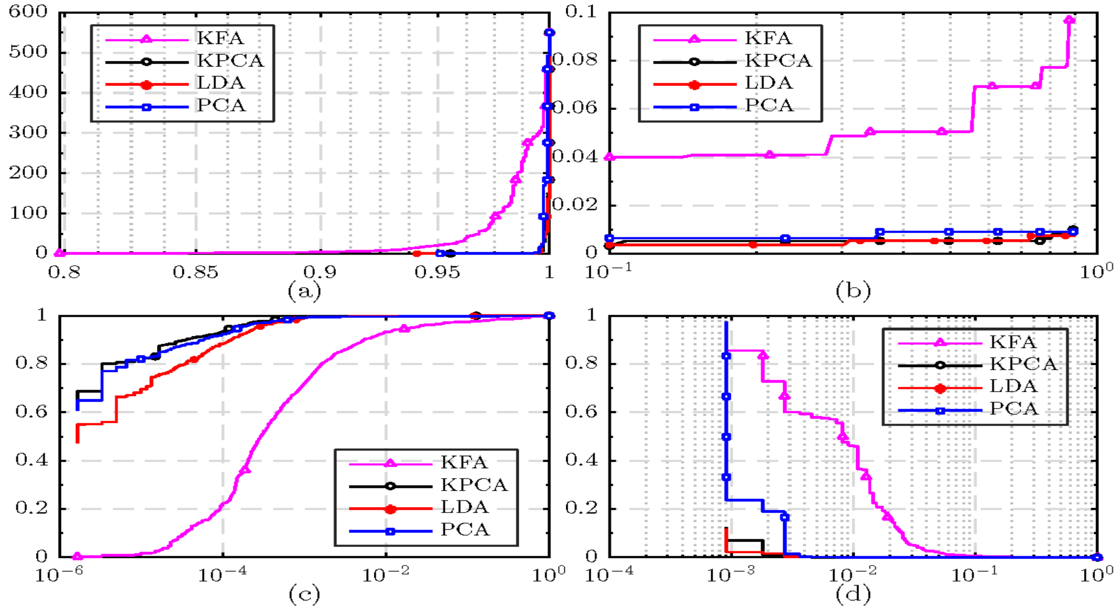

Figure 2: Performance evaluation of the palmprint recognition system using four primary metrics: (a) Cumulative Match Characteristic (CMC); (b) Expected Performance Curve (EPC); (c) Receiver Operating Characteristic (ROC); and (d) Detection Error Tradeoff (DET) across dimensionality reduction methods (KFA, KPCA, LDA, and PCA).

5. Conclusion and Recommendations

This study demonstrates that the combination of dimensionality reduction methods and matching techniques significantly influences the performance of palmprint recognition systems. Experimental results show that the KPCA and Cosine Similarity pairing yields the best performance, achieving a verification rate of 99.455% and an exceptionally low EER of 0.00546. The LDA–Cosine combination also proves highly competitive, with a verification rate of 99.435%. Across all dimensionality reduction approaches, Cosine Similarity consistently delivers optimal results, confirming its effectiveness in measuring directional similarity in biometric feature patterns. In contrast, matching techniques such as Hausdorff and Ndistance exhibit poor performance, with high EERs and verification rates below 55%, making them less suitable for high-accuracy biometric systems.

Based on the findings and analysis, it is recommended that palmprint recognition systems utilize KPCA or LDA in conjunction with Cosine Similarity, especially for applications requiring high precision and low tolerance for errors. Future research can extend this study by evaluating the system on larger and more diverse datasets, including real-world scenarios with varying illumination and hand pose conditions. Additionally, integrating data augmentation techniques and deep learning approaches may further enhance the system's generalization capability. Computational efficiency should also be addressed, particularly for implementation in edge or embedded systems, ensuring the system remains both accurate and lightweight.

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