Image enhancement in palmprint recognition: a novel approach for improved biometric authentication

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ABSTRACT

Several researchers have used image enhancement methods to reduce detection errors and increase verification accuracy in palmprint identification. Divergent opinions exist among experts regarding the best method of image filtering to improve image palmprint recognition. Because of the unique characteristics of palmprints and the difficulties in preventing counterfeiting, image-filtering techniques are the subject of this current research. Researchers hope to create the best biometric system possible by utilizing various techniques. These techniques include image enhancement, Gabor orientation scales, dimension reduction techniques, and appropriate matching strategies. This study investigates how different filtering approaches might be combined to improve images. The palmprint identification system uses a 3W filter, which combines wavelet, Wiener, and weighted filters. Optimizing results entails coordinating the 3W filter with Gabor orientation scales, matching processes, and dimension reduction methods. The research shows that accuracy may be considerably increased using a 3W filter with a Gabor orientation scale of $[8 \times 7]$, the kernel principal component analysis (KPCA) dimension reduction methodology, and a cosine matching method. Specifically, a value of 99.722% can be achieved. These results highlight the importance of selecting appropriate settings and techniques for palmprint recognition systems.

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1. INTRODUCTION

Image enhancement is pivotal in boosting the accuracy and efficiency of biometric systems [1]. With more transparent images and sharper details, systems can identify and verify individual identities more quickly and accurately [2]. Moreover, enhanced images reduce the potential errors that might arise due to background disturbances or noise in the image [3]. In the rapidly evolving realm of biometrics, image enhancement has become a crucial technique [4]. The goal of image enhancement is to improve the visual and aesthetic quality of images and facilitate subsequent processing stages [5]. The world of image enhancement is filled with various methods, each tailored for a specific purpose [6]. Each technique has its advantages and challenges, depending on the nature of the image and the purpose of its processing [7]. For instance, a method suitable for medical images might not be suitable for satellite images [7].

Image enhancement is not a simple process but a complex journey involving various aspects and techniques [8]. In image processing, various dimensions are needed, ranging from adjusting color, contrast, and brightness to noise removal [9]. Each of these dimensions uniquely improves image quality, and choosing the proper technique is crucial to achieving optimal results [10]. One common observation is the complexity and inherent variation in different images [11]. No single image enhancement method can be considered a universal solution for all types of images [7]. Each image has characteristics, from color distribution, contrast, and texture to potential noise [12]. These unique characteristics often require different enhancement approaches. For example, images taken in low light conditions might require brightness and contrast enhancement, while images with much noise might require sophisticated denoising techniques. Furthermore, images taken by cameras with varying resolutions or under different lighting conditions might also require different enhancement approaches. Another challenge is ensuring that image enhancement does not sacrifice original details or introduce unwanted artifacts. Excessive contrast enhancement, for example, can produce images that look unnatural or lose details in shadows and highlights. Image filtering is a crucial step in image processing, especially in the context of palmprint recognition. In the case of palmprint recognition, the image quality becomes a key factor [13]–[15].

Scientists have extensively employed image enhancement techniques to enhance the precision of palmprint recognition verification and decrease detection errors [16]–[18]. Researchers have yet to agree on a reliable and efficient standard image filtering technique for enhancing palmprint images in the context of palmprint recognition [19]. The advancement in image filtering techniques has established a solid foundation for ongoing innovation and research in the field of palmprint biometrics [20]. An emerging method that has attracted much interest is the utilization of composite filters, which mix different types of filters to obtain the highest level of picture quality improvement [21]. Contrast is crucial in determining the clarity of features in palmprint images within this particular environment [17]. Images with high contrast effectively exhibit intricate elements, clearly differentiating between bright and dark regions [22]. Improving picture quality is particularly crucial in palmprint recognition applications, as identification accuracy dramatically depends on the visibility of pattern features [23].

This study aims to improve the contrast of palmprint images using a mixed filter method. This approach combines the advantages of multiple techniques, such as wavelet filters for managing detail and texture, Wiener filters for reducing noise, and weighting algorithms for achieving well-balanced outcomes. This unified approach represents a novel exploration, even though specific components have been previously employed in palmprint identification. Wavelet analysis, specifically multi-wavelet analysis, is crucial for identifying distinctive characteristics from the region of interest (ROI) in palmprint images. Multi-wavelets simultaneously capture symmetry, orthogonality, compact support, and high vanishing moments. The suggested technique demonstrates a remarkable ability to accurately identify palmprints, even when there is interference from noise and misalignment [24]. The Wiener filter eliminates noise artifacts, such as blurring, from iris and palmprint photos, thereby boosting crucial textural regions within the images [25]. The weighting method enhances the initial illumination map by giving weights to various image regions. This process highlights significant areas and reduces noise, hence improving the accuracy of the illumination map estimation [26]. This research endeavours to develop a rapid and superior approach for palmprint recognition by integrating wavelet, Wiener, and weighting techniques (3W). The objective is to expand the limits of biometric recognition capabilities and offer a more precise, efficient, and successful solution for individual identification.

2. METHOD

Biometric authentication has become one of the most trustworthy identifying techniques in the current digital world. Specifically, palmprint recognition has gained significant interest due to its uniqueness and the challenges associated with its forgery. However, the quality of palmprint images can be affected by various external factors such as lighting, humidity, and the type of scanning equipment used. Ambiguities and noise in the images can lead to identification errors, underscoring the need for improved techniques to enhance image quality. In conducting the research, the selection of data sources is crucial. The study utilizes the PolyU database as the primary data source. This database provides a collection of image objects from 600 individuals. Each image from these individuals has ten different appearance variations. In the study, three images are included for training data and three images for testing data. The appropriate selection of sample sizes for training and testing can have a considerable impact on biometrics, just as educational aids can improve students' learning process [27].

Four steps are involved in achieving the final study conclusion, which is the accuracy level of the system: pre-processing, dimension reduction, matching using the distance method, and uniformity layout using the Gabor method. Among these four stages, the pre-processing phase involves image enhancement using a combination of filters. Subsequently, the chosen orientation scale for Gabor is [8×5], dimension reduction is done with principal component analysis (PCA), and matching is conducted using Euclidean. To further enhance the palmprint biometric detection method, future developments will explore other methods, from the choice of Gabor orientation scale, dimension reduction, and distance method.

Image pre-processing is a crucial step to enhance image quality before proceeding to the next phase. Generally, the pre-processing process involving image use is the application of image filters. One such filter is the wavelet filter. The primary reason for using the wavelet filter is its excellent capability to identify and reduce weak signals that might emerge due to noise. Additionally, using wavelet filters offers the added advantage of file size reduction, facilitating storage and transmission processes. Moreover, wavelet filters enhance contrast and details, making images more transparent and recognizable. In addition to the wavelet filter, the pre-processing stage utilizes the Wiener filter. The Wiener filter effectively reduces image noise by considering the statistics of the signal and noise present in the image. As a result, images processed with the Wiener filter exhibit enhanced clarity and maintain their details, even when noise is present. Subsequently, the weighting method becomes an integral part of the pre-processing process. Through the application of the weighting method, the pixel intensity of images can be adjusted to accommodate the unique characteristics they possess. In palmprint recognition applications, the weighting technique helps highlight essential features of the palmprint and reduces the effects of imperfections or noise that might be present. Applying the weighting method also ensures that every detail of the palmprint information is retained and enhanced, thereby improving the efficiency and accuracy of the subsequent recognition process. The integration of various methods to enhance system performance is an approach that is also frequently adopted by other researchers. An example is the application that combines global positioning system (GPS) and computer vision [28]. In this study, since there are three main processes in this pre-processing, namely wavelet, Wiener, and weighting, it can also be referred to as the 3W process.

2.1. Wavelet

For image processing, the wavelet filter can address weak signals due to noise and can also be used to reduce file size. Wavelet variations have multi-resolution characteristics. The signal will produce significant coefficient values around local points and have a high approximation for non-linear signals. The wavelet method can enhance local detail values and global palmprint images [12]. Employing the wavelet method can reduce or even eliminate noise in non-linear mapping [29]. Although it has many advantages, the wavelet method has drawbacks, namely, the computational load of the entire image must be processed, and there is a loss of crucial information during frequency separation. Based on the researcher's opinion, the performance of the wavelet method can be improved when combined with other algorithms as a means of image normalization.

If the value resulting from the normalization process $Y_{(i,j)}$ is applied to the original palmprint image $I_{(i,j)}$, where i and j are the row and column indices of the pixels in the image, then (1) can be used for the entire image n with a minimum value of $\min_v$ and a maximum of $\max_v$. The notation $\lceil \cdots \rceil$ represents rounding up to the nearest whole number.

$$Y_{(i,j)} = \left\lceil \frac{I_{(i,j)} - \min_v}{\max_v - \min_v} \times 255 \right\rceil \tag{1}$$

Furthermore, using the wavelet method on the normalized image $Y_{(i,j)}$ can be expressed in (2).

$$\mathcal{W}_{s_x,s_y,t_x,t_y} = \int\int Y_{(i,j)} \psi\left(\frac{x-t_x}{s_x}, \frac{y-t_y}{s_y}\right) dx\, dy \tag{2}$$

with $Y_{(i,j)}$ being the normalized image. The indices i and j indicate the row and column of the image pixels. $\mathcal{W}_{s_x,s_y,t_x,t_y}$ is the wavelet transformation of the image for the given parameters s_x, s_y, t_x, and t_y. The variables s_x and s_y represent the scaling factor in the x and y directions, while t_x and t_y represent the translation factor in the x and y directions. $\psi\left(\frac{x-t_x}{s_x}, \frac{y-t_y}{s_y}\right)$ is the wavelet function, which is used to analyze the image at different scales and translations. The function ψ is typically chosen based on the type of wavelet transformation being used (e.g., Morlet, Haar, and Daubechies). The double integral $\int\int$ represents the operation of taking the inner product of the image with the wavelet function over the entire image domain. In other words, it is used to measure how much the image $Y_{(i,j)}$ and the wavelet function ψ "match" at a particular scale and translation. If ψ is the wavelet function for the transformation using the 'haar' type in 'symmetric' mode, then to obtain the wavelet coefficient values that describe the image information in the frequency domain, Equation (2) can be rewritten in the form of (3).

$$\mathcal{W}\left(Y_{(i,j)}; \text{'haar'}, \text{'sym'}\right) = (cA, cH, cV, cD) \tag{3}$$

with the values obtained from the wavelet process being the approximation coefficient cA and three detail coefficients cH, cV, and cD, which respectively represent the horizontal, vertical, and diagonal components of the data.

2.2. Wiener

In signal processing and image analysis, it is often necessary to blur or filter data and then attempt to recover the original data from the blurred image. By applying a motion filter to simulate the blurring effects caused by a specific motion, the recovery of the blurred image can be addressed using the Wiener deconvolution method [30]. The Wiener process is required to assess the effectiveness of recovery from damaged images, as well as for noise filtering and enhancing image sharpness [31]. In research for blurring effects due to specific motion, a point spread function (PSF) with a length of 13 and an angle of 13° is applied to each coefficient component using convolution operations and the 'circular' mode, resulting in the values in (4).

$$\widehat{\xi} = \xi * \text{PSF} \tag{4}$$

where ξ represents the wavelet coefficients cA, cH, cV, and cD. Meanwhile, $\widehat{\xi}$ is the new wavelet coefficients from the Wiener filter process, sequentially distributed into $\widehat{cA}$, $\widehat{cH}$, $\widehat{cV}$, and $\widehat{cD}$.

To visualize the PSF filter, in MATLAB, the command `disp(fspecial('motion', 13, 13))` can be used. The PSF filter will produce a diagonal matrix moving from the bottom left to the top right. The highest value of this filter, which is 0.0757, is located in the center of the matrix and symmetrically divides the matrix into left and right. Due to its symmetry, this matrix can be used for smoothing operations that produce consistent effects across the entire image. Additionally, it helps reduce artifacts that might arise from asymmetry and prevents the introduction of bias or distortion in an image.

2.3. Weighting

The weighting method improves the quality of degraded images due to weak lighting. The purpose of the weighting method is to enhance the contrast and clarity of the image by estimating the appropriate lighting map [32]. The weighting method is crucial in obtaining more precise image outputs by considering the intensity differences of pixels within the image. There are three applications of the weighting technique: using total variation minimization, using the gradient of the initial lighting map, and lastly, calculating based on the gradient of the initial lighting maps [26]. From trial and error testing, the optimal weighting value for the palmprint recognition system is 1.5. From (4), the parts multiplied by the weighting value are $\widehat{cH}$, $\widehat{cV}$, and $\widehat{cD}$. Meanwhile, the value of $\widehat{cA}$ is multiplied with the histogram process of the normalized image ($\mathcal{H}_{\mathcal{Y}}$). The final image, resulting from the pre-processing that involves the use of the wavelet, Weiner, and weighting methods ($\hat{I}$), is obtained by the inverse wavelet process from (3) to form (5).

$$\hat{I} = \mathcal{W}^{-1}\left[\mathcal{H}_{\mathcal{Y}}\widehat{cA}, 1.5\widehat{cH}, 1.5\widehat{cV}, 1.5\widehat{cD}\right] \tag{5}$$

with $\mathcal{W}^{-1}$ denotes the inverse wavelet transform operation.

Subsequently, from the image that has been filtered with 3W, namely the image $\hat{I}$, further processing is carried out using the Gabor scale (ϕ) and orientation (κ) methods, dimension reduction, and distance matching methods. Selecting the appropriate image filter method, determining the Gabor orientation scale, applying suitable dimension reduction techniques, and using accurate distance methods will create an optimal biometric system [33]. The palmprint recognition system's advantage is that it meets the criteria with low values for FRR, FAR, and EER and has a high value for verification. In brief, false rejection rate (FRR) is how often the system incorrectly denies access that should be granted. False acceptance rate (FAR) is how often the system incorrectly grants access that should not be given. Equal error rate (EER) is where FRR and FAR have the same value. The EER means the risk of the system mistakenly denying legitimate access is equal to the risk of the system mistakenly granting access to those who are not entitled. Meanwhile, verification is checking and ensuring the claimed ownership is something legitimate. In the context of digital security and biometrics, verification specifically refers to validating someone's identity based on unique information or characteristics they possess. Subsequently, from these biometric measurements, four curves will be produced, namely ROC, EPC, DET, and CMC. Receiver operating characteristic (ROC) is a curve that shows how great the system's probability of correctly detecting without errors is. The higher and more to the left this curve is, the better the detection system. Detection error trade-off (DET) is a curve that shows how often the system correctly identifies objects compared to how often it is incorrectly identified. Equal error rate (EPC) is a curve that shows how often the system identifies correctly and incorrectly in various situations. Lastly, cumulative match characteristic (CMC) is a curve that shows the probability of correct identification within the testing repetition limits.

3. RESULTS AND DISCUSSION

In the study, four tests were conducted to achieve the smallest possible EER value and the highest possible verification value: changing filter parameters, Gabor orientation scale, dimension reduction, and matching method. Using the original PolyU palmprint image for both training and testing with three samples each and employing the Gabor [8×5] parameter, PCA reduction method, and Euclidean matching method, the results showed an FRR of 0.01167, FAR of 0.01169, EER of 0.01168, and an accuracy rate of 98.83333%.

When the modified Gabor parameter [8×7] was used, the outcomes were an FRR of 0.01056, FAR of0.01034, EER of 0.01045, and a verification rate of 98.94444%. A comparison of different scales (ϕ) orientation (κ) Gabor can be seen in the EPC curve in Figure 1(a). From the curve in Figure 1(a), the black line representing the Gabor method with $\phi = 8$ and $\kappa = 7$ indicates that both the false alarm probability and miss probability values are very close to zero.

The study explored suitable dimension reduction techniques ($\mathcal{RD}$) for palmprint recognition. Utilizing parameters such as the original palmprint image, a Gabor orientation scale of $[8 \times 5]$, and four dimension reduction methods (kernel fisher analysis (KFA), KPCA, linear discriminant analysis (LDA), and PCA) combined with the Euclidean matching method, the research outcomes are detailed in Table 1. This is further illustrated in the curve of Figure 1(b). From the curve, it is evident that the $\mathcal{RD}$ KPCA, represented by the black line, outperforms the KFA, LDA, and PCA methods. As evident from Table 1, both KPCA and LDA methods yield an $\mathcal{RD}$ verification value of 99.111000%. However, by varying the image filters, adjusting the choices of ϕ and κ for Gabor, or applying different distance methodologies, the KPCA $\mathcal{RD}$ method proves more effective than LDA. The advantage of the KPCA method becomes particularly evident when the research involves images processed with the 3W filter, a Gabor orientation scale of $[8 \times 7]$.

Table 1. The research results of the chosen dimension reduction method parameter from palmprint images using the original ROI for training and testing data with three samples

$\mathcal{RD}$	FRR	FAR	EER	Verification (%)
KFA	0.22667	0.22689	0.22678	77.33300
KPCA	0.00889	0.00889	0.00889	99.11100
LDA	0.00889	0.00885	0.00887	99.11100
PCA	0.01167	0.01169	0.01168	98.83300

The subsequent research focused on determining the best distance method. In this study, seven distance methods were compared, namely Euclidean, CityBlock, Cosine, MahCos, ModEuc, Hausdorff, and Ndistance. The other parameters remained consistent, using the original ROI palmprint data source, ϕ, κ Gabor [8×5], and the PCA dimension reduction method. Based on the test results, the Cosine method provided the best results with an FRR value of 0.00667, FAR 0.00664, EER 0.00665, and a verification rate of 99.33333%. A comparison of the seven matching methods can be seen in Figure 1(c).

The next step in this research was to return to the initial phase to determine the best verification value in the palmprint recognition process by comparing various image filters. In this study, seven image filters were compared: original, anistropic, multiple, shock, skeleton, 3W, and histogram. Other parameters used were the Gabor orientation scale [8×5], the PCA dimension reduction method, and the Euclidean matching method. Based on the test results, the 3W filter proved to be the most effective, yielding values of FRR 0.00556, FAR

0.00554, EER 0.00555, and a verification rate of 99.44444%. The performance comparison between the filters can be seen in the curve of Figure 1(d). Based on the CMC curve in Figure 1(d), the 3W filter method, represented by the yellow line, shows the highest rank value compared to the recognition rate.

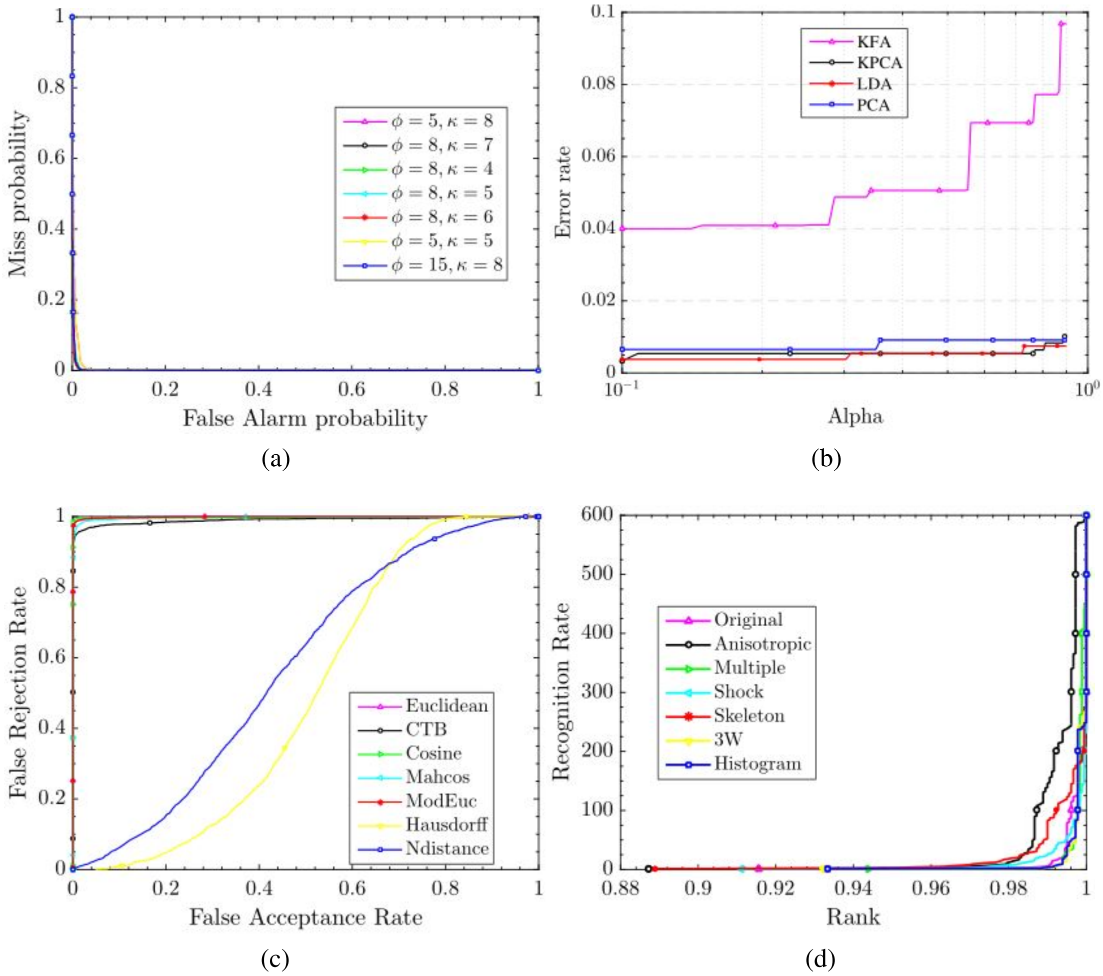

Figure 1. Variations in values for palmprint pattern recognition research (a) the DET curve compares different Gabor orientation scales; (b) the EPC curve exhibiting the advantage of the KPCA dimension reduction method over alternative approaches; (c) the ROC curve depicts the efficacy of different distance-matching methods in palmprint pattern recognition; and (d) the CMC curve compares various palmprint image filtering methods

From the various parameters selected for the palmprint recognition process, image enhancement with the 3W filter yields the highest verification value. It outperforms adjustments to the Gabor orientation scale at [8×7], the KPCA technique, or the cosine matching method, as presented in Table 2. Although the EER and verification values between the 3W filter setting and cosine are identical, the FRR from the 3W filter is lower. A low FRR indicates that the system effectively recognizes legitimate users, which is crucial for applications requiring rapid access; moreover, the 3W filter results in a lower FAR than the cosine method. A low FAR signifies the system's high reliability in preventing unauthorized access, an essential characteristic of security systems. Computational complexity is influenced by the dimension reduction technique selected during calculation. As may be observed in Figure 2, KPCA exhibits the highest verification accuracy. Thus, KPCA can be used as a substitute for the PCA approach in a practical system arrangement.

Multiple test factors were used in order to enhance the study. The results of applying the 3W filter approach, a [8×7] Gabor orientation scale, KPCA dimension reduction, and cosine matching were 0.00278 for the FRR, 0.00278 for the FAR, and 0.00278 for the EER, with a verification rate of 99.722%. The quantity of palmprint image samples affected the EER and verification values in addition to parameter selection. Table 3 makes this clear: there are still three samples used for testing and training. The most incredible verification value was obtained with 450 image objects, followed by a drop, using the 3W image, [8×7], KPCA, and cosine.

Table 2. Comparison of various parameters and their impact on palmprint recognition metrics

Parameter	FRR	FAR	EER	Verification (%)
Filter 3W	0.00556	0.00554	0.00555	99.44444
Gabor [8 × 7]	0.01056	0.01034	0.01045	98.94444
KPCA	0.00889	0.00889	0.00889	99.11100
Cosine	0.00667	0.00664	0.00555	99.44444

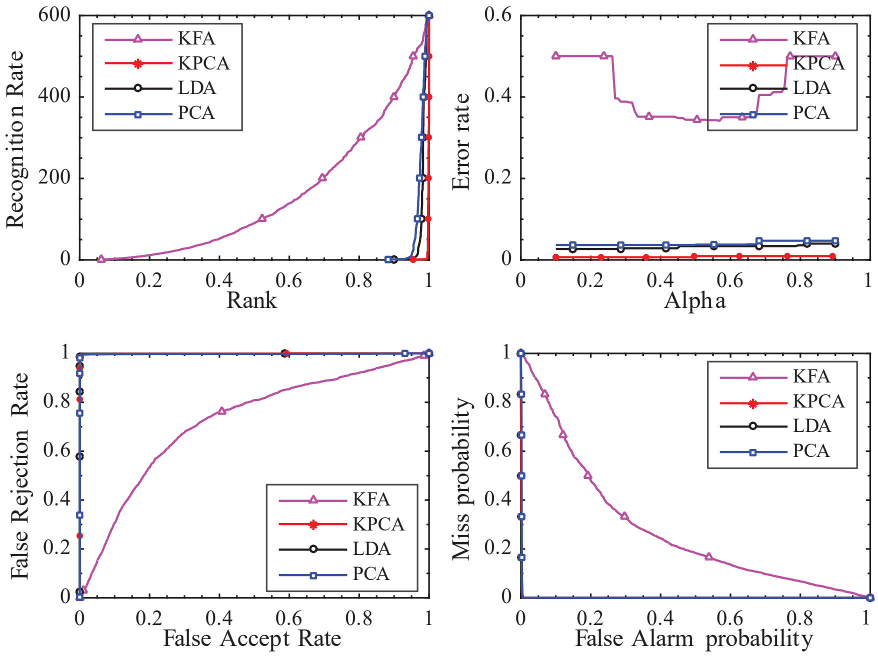

Figure 2. Four biometric curves, namely CMC, EPC, ROC, and DET, are used to reinforce the argument for choosing KPCA over KFA, LDA, and PCA

Table 3. In palmprint recognition, the number of research samples influences system performance

Sample	FRR	FAR	EER	Verification (%)
100	0.00333	0.00313	0.00323	99.667
200	0.00500	0.00499	0.00500	99.500
300	0.00333	0.00332	0.00333	99.667
400	0.00333	0.00333	0.00333	99.667
450	0.00222	0.00228	0.00225	99.778
600	0.00278	0.00278	0.00278	99.722

4. CONCLUSION

In the pursuit of enhancing the accuracy of palmprint recognition systems, various parameters such as image filters, Gabor orientation scales, dimension reduction techniques, and matching methods were tested. From the research findings, using the original PolyU palmprint image with Gabor parameters [8×5] , the PCA reduction method, and the Euclidean matching method resulted in an accuracy of 98.83333%. It was modifying the Gabor parameter to [8×7] improved accuracy to 98.94444%. Among the four dimension reduction methods tested, KPCA demonstrated the best performance with an accuracy of 99.11100%. The cosine matching method yielded results nearly identical to the 3W filter regarding EER and verification. However, the 3W filter exhibited a lower FRR, indicating its superior capability in recognizing legitimate users. Utilizing an optimal parameter combination, namely the 3W filter, Gabor orientation scale [8×7], KPCA reduction method, and cosine matching method, the highest accuracy achieved was 99.722%. The number of palmprint image samples used also influenced the EER and verification values. With a constant training and testing count of 3, increasing the sample count led to variations in EER and verification values.

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