Improvement Palmprint Recognition System by Adjusting Image Data Reference Points

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Abstract. Nowadays, the palmprint recognition method is an attractive tool for people recognition besides face recognition and fingerprint. To get a good palmprint recognition system requires a series of algorithms that are united and worked together to create a preferred method. The biometric system in palmprint recognition is said to be preferred when the choice of the algorithm applied has the advantage of each phase. Generally, The palmprint recognition system starts from the selection of image filters, image positioning, dimension reduction, and finally, end with the distance method. Image normalization position is a problem for researchers because the palmprint is always moving and shows a curved shape making it difficult for the system in the identification and verification process. For this reason, the research focuses on the selection of orientation scale operator value from the Gabor technique to get the best parameter value for palmprint biometrics. The desired system is when the overall performance of the algorithm used will produce an output with a low EER value and a high level of verification. From the research that has been carried out, the range of 8 × 5 becomes a good alternative for the choice of Gabor value pairs.

1. Introduction
A palmprint recognition has become a fabulous topic of interest researchers. From some parts of biometric perception, the palmprint system promises encouraging results so the later can be used to replace the universal fingerprint recognition. With benefit to large-sized, the palmprint is cheap, easy installment and also fast in processing so that it can be used for human identification tool independently or cooperation with other biometric fields to further strengthen the verification process.

Researches in the field of biometric have characterized several subsections containing algorithms to facilitate the individual recognition process is fast, efficient, and has high gain accuracy. One way to approach this goal is to improve an image position and reduce feature information yield from increasing the number of input data. Researcher [1–4] have conducted a study involving the use of filters to improve the image contrast of palm ROI. With the amount of data in a database that is continually growing in number, hence the need for a stable position so all the image have the same reference so that can accelerate and simplify the subsequent process. Some researchers have used the orientation and scale Gabor method to attain a unified position for all data. Meanwhile [5–7] have been using the parameters for expectation reach optimum biometric system. Also [7] uses the dimension reduction of Fisher linear discriminant, [8] uses
the termed kernel locality-constrained collaborative representation based discriminant analysis (KLCR-DA), and [9] uses theoretical slow feature discriminant analysis (SFDA).

All of the researchers who have discussed all kinds of method to achieve higher accuracy and efficiencies process in biometrics field would not agree in one solution of the algorithm method that can solve all the problem in analyzing the palms recognition. Until now researchers always suggests the most appropriate ways to resolve the issues, so that they are introducing a new proposal. Generally, the researchers agreed in two main criterias in terms of leading method: the speed of the process and high accuracy. In the high accuracy has two rules: low in error equal rate (EER) and high in percentage in the verification process. Reaching the primary goal, then many researchers to innovate by combining a variety of algorithms in all stages of the biometric processing that can be proved by several curve namely ROC, CMC, EPC, and DET where for another observer can search the method quickly. Because of biometric recognition is an obstacle every nation then would be highly advisable to use open source data so every person can use the same source. Thus diversify the methods can be minimized, and all parties can accept the concepts.

For that explanation, the authors submit a proposal that involves almost all stages of the biometric recognition scheme to achieve better results in terms of the EER rate and little of consuming time that needed to accomplish the work. Processing begins with the filter process all item in the database by wavelet and continues with the skeleton method, followed by selecting the numeric value of the orientation and scale Gabor. Then the selection of dimension reduction that suits the parameter Gabor and finally for matching stage by using the Cosine Mahalanobis. For all the proposed algorithms, of course, should have a significant impact on the EER rate and verification percentage that can be shown in four different curves where all research using three distinct databases. Finally, an improvement of palmprint recognition can be reached by using Gabor parameters and selecting the dimension reduction method.

2. Research Methods

Some of the problem in palmprint recognition is all the processing requires a stable reference point, and some of palms main lines has similarities so need variations in each image. Gabor filter is widely used in the application of pattern analysis with benefit withstand from changing of illumination, rotation, scale, and translation [10]. In the spatial area, the 2D Gabor filter is a Gaussian kernel function modulated by complex sinusoid waves defined as shown in Equation (1).

$$
G(x, y) = \frac{f^2}{\pi \gamma \tau} \exp \left( -\frac{x'^2 + \gamma^2 y'^2}{2 \sigma^2} \right) \exp \left( j 2\pi f + \varphi \right)
$$

\begin{align*}
x' &= x \cos \theta + y \sin \theta \\
y' &= -x \sin \theta + y \cos \theta,
\end{align*}

with \( f \) is the frequency sinusoid, \( \theta \) is a representation of orientation Gabor, \( \varphi \) is offset value, \( \tau \) is a standard deviation from Gaussian envelope, and \( \gamma \) is scale Gabor. To reduce the number of images from the Gabor results is necessary to apply a down-sampling method. For example, an image with size \( 256 \times 256 \), use the orientation and scale of Gabor parameters \( 8 \times 5 \) and then applying down-sampling \( 8 \times 8 \), then the final Gabor results are \( \frac{256 \times 256 \times (8 \times 5)}{(8 \times 8)} = 40960 \).

Vector feature of Gabor results is still huge after down-sampling process; therefore it is a necessary additional method to reduce again. Generally, a dimension reduction is the additional method.

In general, the normalization of differences in the scale and orientation of the image using the Gabor method. Some researchers who have used the Gabor method as a starting point for operating operations for all image positions include [11–13]. Besides being able to be used as a reference point for the overall image data, the Gabor technique can also be used to obtain
important information in different periods caused by differences in orientation and scale. This principle is the development of the short windowed time Fourier transform technique. Researcher Sung states that the benefit of using Gabor orientation and scale is to normalize positions between images [14]. Wang strengthened this opinion by saying that the use of the Gabor method was able to improve the feature of information on local distortion [15]. Another method for obtaining performance of Gabor is to use an unordered parameter selection. That is the value of the order of scale and orientation when calculating loops in the Gabor system. By Haralick stated that the feature of information from the Gray level co-occurrence Matrix could be improved by using the option of entropy values that are not sequential [16]. Perez then developed Haralick by stating that the choice of values not in order from the scale and orientation of Gabor was able to improve the biometric system [17].

After the image normalization process is complete, the next process is to reduce the amount of data that is not needed. The method of reducing data that is not required or known as the dimension reduction process is a significant problem of the performance and efficiency of the biometrics recognition because it is closely related to computing systems. In general, important feature information needed to recognize someone has a much smaller amount of data compared to the original amount of data. The feature extraction technique in the dimension reduction method has an important task to explore the small feature information, so that enables to represent the whole data dimension. The first step is to align the high-dimensional data with the possible space so two point data with different location can be paired. Further, the task of dimension reduction is to provide infrastructure or parametric mapping between higher-dimensional space to a lower-dimensional area. Various methods are used for machine learning, that is principal component analysis (PCA), kernel principal component analysis (KPCA), linear discriminant analysis (LDA), and kernel Fisher analysis (KFA). Before the dimension reduction method takes place, then a weighting process which aims to maintain the data of the original structure while in latent space. To reduce the influence of Kullback-Leibler divergence, the process is continued by reducing the amount of information available by minimizing dimensional data [18]. Individually, the distance two points are transformed into a probability with an isotropic Gaussian on all data-point $i$ can be described in Equation (2), with a density point $j$ under the Gaussian and then renormalizes to produce the conditional probability $P_{ij}$.

$$P_{ij} = \frac{\exp \left(-\frac{||x_i - x_j||^2}{2\sigma_i^2}\right)}{\sum_{k \neq i} \exp \left(-\frac{||x_i - x_k||^2}{2\sigma_i^2}\right)}. \quad (2)$$

The Gaussian variance $\sum_i$ arranged so that the complexity (perplexity) for each the conditional distribution of $P_i$ is same, and $P_{ij}$ arranged to zero. To make more accessible calculate the parameter numbers needed in the system, then need to use the perplexity parameter which has a free value taken from the range of neighboring pixel values. To establish a single connection Gaussian value $s$ then it is necessary to make the symmetry of the conditional probability $P_{ij}$ by setting it to $P_{ij} = P_{ji}/P_{ij}$. The result is a probability connection of $P_{ij}$ which measures the similarity between the data points between $i$ and $j$ as a result of a relatively small Gaussian variation.

To measure the similarity of pairs $i$ and $j$ in latent space, then using a centralized symmetrical distribution method. The density of all $j$ points in the distribution is obtained from the normalized values of $Q_{ij}$ so that become candidates that will represent the local data structure in that potential space. The next weighting is to use the minimum difference Kullback-Leibler between the probability distribution $P$ and $Q$ which can be written with the Equation (3).

$$C = KL(P||Q) = \sum_{i \neq j} P_{ij} \log \frac{P_{ij}}{Q_{ij}}. \quad (3)$$
The distribution value that contains the pair similarity of the Gaussian $Q_{ij}$ in potential space tends to crowd defects value. In general, the problem of crowding defects occurs because of the difference in high and low dimensional volumes. If there is no data in the potential space or data that is smaller than the space to be paired, the connection fails. This problem occurs because the dimensions to be modeled become very large. It is necessary to add extra values that connect the two spaces which also to minimize the occurrence of crowding defects. The general method used to balance data from high dimensions to low dimensions is to use a dimensional reduction algorithm. Dimension reduction is the construction of low dimensional data representation that still has a significant impact on its partners in high dimensional space. From a pattern recognition perspective, dimension reduction is an effective method for avoiding dimensional problems and increasing the efficiency of pattern matching. Therefore if the system has a large volume in high dimensions, then the problem of choice of dimensional reduction techniques is an important issue that should be the primary concern of researchers.

Researchers have developed a lot of dimension reduction technique for the palmprint recognition. In general, the researchers grouped dimensional reduction techniques in two categories: linear and non-linear. Reduction of linear dimensions trying to find sub-space low dimensional that still have meaning in high proportion. The sub-space can provide a complete representation from high size when the data structure is added or embed within the linear input. The PCA and LDA are two methods of learning machine or dimension reduction in linear-based that have been widely known, mainly in computer vision and become a favorite technique for face, palmprint recognition and other biometric [11]. In reality, the linear model sometimes fails to find the critical feature information in high data with a different class. Some non-linear dimension reduction technique has been developed to address the problem. A kernel method is part of the support vector machine (SVM) with a general task is to find and study a type of relations for example cluster, principal component, classification, a correlation in datasets. The kernel method is the representation of the non-linear problem with enable to operate in high dimension by merely computing the inner products between the images of all pairs. The KPCA and KFA are an example to the system and have been widely used for the biometric recognition [8]. After the dimension reduction process, the next stage of the palmprint recognition system is the matching process.

The similarity method is a technique of comparing two vectors with mathematical operations to find out the range of values close to one another. Two vectors are said to be the same if the difference between them is zero. The matching process in the palmprint recognition method is done by first grouping the value of features in a group. Between features are then grouped with other data that has a value link or shorter distance. The same data will have a close orientation distance, and vice versa for different objects have a significant correlation distance (least square). In the palmprint recognition matching method that is widely used by researchers is the Euclidean technique [19,20]. The advantage of using the Euclidean method is the simplicity of the function, the ability to find a unique and sturdy scope of settlement in resolving capital that differs significantly [21]. Even though it has advantages, Fails stated that the use of the Euclidean method has the disadvantage of not including consistent attribute correlation value coverage. Therefore, Qian improved the Euclidean process by using the cosine method, which is suitable for the use of palmprint recognition [22].

3. Results and Discussions
For this research uses three classes database contain the image of palms, namely: Casia accommodate 650 model, IITD India = 450, and PolyU = 550. For each level has some variations 5,6, and 10 respectively. A total number of images used for the study were 11450 in the form of rectangular ROI (region of interest) with the size of 256 × 256 in jpg extension. Simulation algorithms use PC with Intel i7 4500k and 16 Gb of main memory.
The initial process is to filter all images in the database using the wavelet method. The output of the wavelet method will produce three detailed values and one approximation value. In research only uses approximation values and removes three detailed values which are then further processed using a skeleton filter. Each the class get the same treatment that is by multiplying number a scale $\kappa$ and an orientation $\varphi$ of Gabor technique. For example, the Casia database with the object of the image is 650 then using Gabor parameter with $\kappa = 5$ and $\varphi = 7$ will generate 113750 total new images. This is why the Gabor process always involves big data that cause complicated processing time, but have the advantage in research results that is lesser of EER rate.

Tables 1, 2 and 3 are the values of the research results. From the table, the process time in the study has a time variation due to the selection of different Gabor orientation scales. From Table 1 indicates that the KPCA method with Gabor parameters of $8 \times 5$ is remarkable with approximately 1.27998 second. The dimension reduction of KPCA is also the best choice when using the database of IITD India with the $8 \times 3$ of Gabor parameter selection that is 0.34701 s. While in Table 3 shows that the KPCA method remains the best selection of the dimension reduction that would result in 0.62946 s when using the scale and orientation Gabor of $5 \times 3$. On the contrary, the LDA method is the worst choice when coupled with Gabor parameters as evidenced by the longest processing time compared with three other dimension reduction methods.

\[ \begin{array}{c|c|c|c|c}
\hline
\kappa & \varphi & \text{Time} \\
\hline
5 & 8 & 1.27998 \\
4 & 5 & 0.34701 \\
3 & 8 & 0.62946 \\
5 & 3 & 1.27998 \\
3 & 8 & 0.34701 \\
5 & 3 & 0.62946 \\
8 & 15 & 1.27998 \\
8 & 3 & 0.34701 \\
8 & 8 & 0.62946 \\
15 & 8 & 1.27998 \\
\end{array} \]

Figure 1: ROC curve (receiver operating characteristic) indicating the reliability of a system with a line curved shapes rising from the bottom left side and move straight to the top position. Visible the Gabor parameters with cyan color, namely $\varphi = 8$ and $\kappa = 5$ is superior to the three-part in (a) KPCA, (b) PCA, and (d) LDA while for (c) or KFA method in right if it uses the parameter of $15 \times 5$.

Figure 1-4 shows four types of biometric performance curves obtained from research results. As shown in Figure 1 for the ROC curve contains seven pairs of orientation techniques and Gabor scale which are displayed in four different dimensions reduction methods. At a glance, curves Figure 1 (a) or in KPCA-based modes have the best graphics patterns, while curves Figure 1 (c) or KFA-based are the lowest ROC curves. Instead, the ROC curve is the CMC curve as shown
Table 1: The Casia database containing the image of palm as much as 650 people with variations of each object is five times.

| Method | Gabor time | FRR  | FAR  | EER  | Ver.  |
|--------|------------|------|------|------|-------|
| KFA    | 15 × 8     | 0.52676 | 0.42556 | 0.42471 | 0.42513 | 57.444 |
|        | 5 × 8      | 0.52676 | 0.42556 | 0.42471 | 0.42513 | 57.444 |
|        | 5 × 4      | 0.51472 | 0.43111 | 0.43168 | 0.4314  | 56.889 |
|        | 5 × 3      | 0.60896 | 0.42778 | 0.42778 | 0.42778 | 57.222 |
|        | 8 × 5      | 0.47308 | 0.44111 | 0.44084 | 0.44098 | 55.889 |
|        | 8 × 3      | 0.70563 | 0.13778 | 0.13778 | 0.13778 | 86.222 |
|        | 8 × 8      | 0.96728 | 0.12667 | 0.12703 | 0.12685 | 87.333 |
| KPCA   | 15 × 8     | 0.37459 | 0.04667 | 0.04655 | 0.04661 | 95.333 |
|        | 5 × 8      | 0.37459 | 0.04667 | 0.04655 | 0.04661 | 95.333 |
|        | 5 × 4      | 0.37197 | 0.05778 | 0.05796 | 0.05787 | 94.222 |
|        | 5 × 3      | 0.49656 | 0.04333 | 0.04355 | 0.04344 | 95.667 |
|        | 8 × 5      | 0.34701 | 0.05  | 0.05012 | 0.05006 | 95   |
|        | 8 × 3      | 0.46325 | 0.05667 | 0.05656 | 0.05661 | 94.333 |
|        | 8 × 8      | 0.57332 | 0.06111 | 0.06085 | 0.06098 | 93.889 |
| LDA    | 15 × 8     | 1.38771 | 0.05444 | 0.05437 | 0.0544  | 94.556 |
|        | 5 × 8      | 1.38771 | 0.05444 | 0.05437 | 0.0544  | 94.556 |
|        | 5 × 4      | 1.03538 | 0.06667 | 0.0669  | 0.06678 | 93.333 |
|        | 5 × 3      | 2.09833 | 0.05556 | 0.05579 | 0.05567 | 94.444 |
|        | 8 × 5      | 1.36903 | 0.06111 | 0.06065 | 0.06088 | 93.889 |
|        | 8 × 3      | 2.98785 | 0.05444 | 0.05438 | 0.05441 | 94.556 |
|        | 8 × 8      | 5.16903 | 0.05333 | 0.05265 | 0.05299 | 94.667 |
| PCA    | 15 × 8     | 0.90162 | 0.08333 | 0.08269 | 0.08301 | 91.667 |
|        | 5 × 8      | 0.90162 | 0.08333 | 0.08269 | 0.08301 | 91.667 |
|        | 5 × 4      | 0.76795 | 0.10667 | 0.1067  | 0.1068  | 89.333 |
|        | 5 × 3      | 1.52668 | 0.06556 | 0.0656  | 0.0656  | 93.444 |
|        | 8 × 5      | 0.97712 | 0.07667 | 0.07629 | 0.07648 | 92.333 |
|        | 8 × 3      | 2.17595 | 0.06111 | 0.06102 | 0.06107 | 93.889 |
|        | 8 × 8      | 3.75657 | 0.06  | 0.05992 | 0.05996 | 94   |

in Figure 2 which has an inverse direction with Figure 1 where ideal CMC curves are in Figure 2 (a) and Figure 2 (d).

The curve perspective for the ROC type and the CMC curve still has weaknesses that are difficult to choose because the lines are solid with each other. For this reason, the depiction of performance is done by dividing horizontally (EPC curve) and vertically (DET curve). On picture. 3 (a), (b), and (d) with the color of the cyan line located at the far left. This shows that the cyan or representative line is 8 × 5. The Gabor parameter is the best option compared to the PCA, KFA, and LDA methods. The most obvious form for investigating the critical point of system optimization is every time the EPC curve is used as shown in Figure 4. In the curve, it appears that lines with cyan colors or Gabor representations of 8 × 5 are the most optimal dimensional reduction systems. Instead, the KFA method in Figure 4 (c) is the worst dimensional reduction system that works together with Gabor parameters.

In the term of optimization that the system used, the Table 1 to 3 shows that the dimension reduction of KPCA method is preferable to use compared with other methods such as KFA, LDA, and PCA. With the Casia database selection, obtained the rate optimization of EER is 0.05313 and 0.94692 percent for verification value. The standard provisions apply in terms of optimizing the biometric recognition system, that is, if the study gets an EER value that gets
Table 2: The IITD-India database containing the image of palm as much as 450 people with variations of each object is six times.

| Method | Gabor time | FRR  | FAR  | EER  | Ver.  |
|--------|------------|------|------|------|-------|
| KFA    | 15 × 8     | 0.58755 | 0.42111 | 0.42158 | 0.42135 | 57.889 |
|        | 5 × 8      | 0.52676 | 0.42556 | 0.42471 | 0.42513 | 57.444 |
|        | 5 × 4      | 0.51472 | 0.43111 | 0.43168 | 0.4314  | 56.889 |
|        | 5 × 5      | 0.47308 | 0.44111 | 0.44084 | 0.44098 | 55.889 |
|        | 8 × 3      | 0.70563 | 0.13778 | 0.13778 | 0.13778 | 86.222 |
|        | 8 × 8      | 0.96728 | 0.12667 | 0.12703 | 0.12685 | 87.333 |
| KPCA   | 15 × 8     | 0.47575 | 0.07111 | 0.0711  | 0.07111 | 92.889 |
|        | 5 × 8      | 0.37459 | 0.04667 | 0.04656 | 0.04661 | 95.333 |
|        | 5 × 4      | 0.37197 | 0.05778 | 0.05796 | 0.05787 | 94.222 |
|        | 5 × 3      | 0.49656 | 0.04333 | 0.04355 | 0.04344 | 95.667 |
|        | 8 × 5      | 0.34701 | 0.05  | 0.05012 | 0.05006 | 95 |
|        | 8 × 8      | 0.57332 | 0.06111 | 0.06065 | 0.06088 | 93.889 |
| LDA    | 15 × 8     | 2.43634 | 0.05889 | 0.05906 | 0.05906 | 94.111 |
|        | 5 × 8      | 1.38771 | 0.05444 | 0.05437 | 0.0544  | 94.556 |
|        | 5 × 4      | 1.03538 | 0.06667 | 0.0669  | 0.06678 | 93.333 |
|        | 5 × 3      | 2.09833 | 0.05556 | 0.05579 | 0.05567 | 94.444 |
|        | 8 × 5      | 1.36903 | 0.06111 | 0.06065 | 0.06088 | 93.889 |
|        | 8 × 3      | 2.98785 | 0.05444 | 0.05438 | 0.05441 | 94.556 |
|        | 8 × 8      | 5.16903 | 0.06111 | 0.06065 | 0.06088 | 94.667 |
| PCA    | 15 × 8     | 1.54444 | 0.07444 | 0.07415 | 0.0743  | 92.556 |
|        | 5 × 8      | 0.90162 | 0.08333 | 0.08269 | 0.08301 | 91.667 |
|        | 5 × 4      | 0.76795 | 0.10667 | 0.1067  | 0.1068  | 89.333 |
|        | 5 × 3      | 1.52668 | 0.06556 | 0.06565 | 0.0656  | 93.444 |
|        | 8 × 5      | 0.97712 | 0.07667 | 0.07629 | 0.07648 | 92.333 |
|        | 8 × 3      | 2.17595 | 0.06111 | 0.06102 | 0.06107 | 93.889 |
|        | 8 × 8      | 3.75657 | 0.06  | 0.05992 | 0.05996 | 94 |

smaller than the better the system. The same thing also refers to the verification value, that is the higher value it means more remarkable the algorithm. Furthermore, the use of IITD India database, the amount of EER and verification is equal to 0.04344 and 95.667% with the KPCA method. Meanwhile, when using the PolyU database, the KPCA method still remains the best value with 0.00835 for EER and 99.182% for a verification process.

The final value of the research is through a series activity start from image filter processes, positioning with the Gabor method, dimensional reduction with KPCA, until matching operations with the cosine system. The image enhancement process can increase the level of contrast of various backgrounds of different people’s tread images. After the method normalizes the color of the object of research, the research process continues by finding reference points between image data that have different directions and scales. The Gabor method emphasizes the similarity of the position of all data. Although it has weaknesses with increasing processing time, the use of Gabor techniques can improve the verification process. The Gabor core size is twice the size of the image. In the research, the Gabor core use 32-bit size so that the calculation size of Gabor’s dimensions is from minus 32 to plus 31. Estimation of orientation and scale used sequence series values ranging from 0 to initial value with an incremental amount of 1. For example, if $\varphi = 8$ and $\kappa = 5$ then for one image the data will be 40 times. To
Table 3: The PolyU database containing the image of palm as much as 550 people with variations of each object is ten times.

| Method | Gabor time | FRR     | FAR     | EER     | Ver.   |
|--------|------------|---------|---------|---------|--------|
| KFA    | 15 × 8     | 1.03788 | 0.4072  | 0.4072  | 0.4072 | 59.273 |
|        | 5 × 8      | 0.8208  | 0.4618  | 0.4610  | 0.4614 | 53.818 |
|        | 5 × 4      | 0.8380  | 0.4154  | 0.4144  | 0.4151 | 58.345 |
|        | 5 × 3      | 1.0521  | 0.4147  | 0.4145  | 0.4145 | 58.545 |
|        | 8 × 5      | 0.8871  | 0.4030  | 0.4029  | 0.4029 | 59.727 |
|        | 8 × 3      | 1.1673  | 0.4484  | 0.4483  | 0.4484 | 55.182 |
|        | 8 × 8      | 1.5253  | 0.3498  | 0.3499  | 0.3499 | 65.518 |
| KPCA   | 15 × 8     | 0.6742  | 0.0190  | 0.0190  | 0.0190 | 98.109 |
|        | 5 × 8      | 0.6802  | 0.0145  | 0.0145  | 0.0145 | 98.545 |
|        | 5 × 4      | 0.6294  | 0.0148  | 0.0147  | 0.0147 | 98.545 |
|        | 5 × 3      | 0.7496  | 0.0081  | 0.0085  | 0.0085 | 99.182 |
|        | 8 × 5      | 0.6900  | 0.0135  | 0.0138  | 0.0138 | 98.818 |
|        | 8 × 3      | 0.9775  | 0.0118  | 0.0118  | 0.0118 | 98.818 |
|        | 8 × 8      | 0.8871  | 0.0091  | 0.0091  | 0.0091 | 98.545 |
| LDA    | 15 × 8     | 3.0392  | 0.0246  | 0.0246  | 0.0246 | 97.545 |
|        | 5 × 8      | 1.8279  | 0.0201  | 0.0200  | 0.0200 | 98.091 |
|        | 5 × 4      | 1.6272  | 0.0267  | 0.0269  | 0.0269 | 97.273 |
|        | 5 × 3      | 2.7326  | 0.0135  | 0.0136  | 0.0136 | 98.836 |
|        | 8 × 5      | 2.0193  | 0.0154  | 0.0154  | 0.0154 | 98.455 |
|        | 8 × 3      | 4.1609  | 0.0136  | 0.0136  | 0.0136 | 98.636 |
|        | 8 × 8      | 1.4240  | 0.0290  | 0.0290  | 0.0290 | 97.091 |
| PCA    | 15 × 8     | 2.0391  | 0.0363  | 0.0364  | 0.0364 | 96.364 |
|        | 5 × 8      | 1.3285  | 0.0418  | 0.0418  | 0.0418 | 95.818 |
|        | 5 × 4      | 1.1852  | 0.0519  | 0.0519  | 0.0519 | 94.909 |
|        | 5 × 3      | 2.0064  | 0.0201  | 0.0198  | 0.0198 | 98.091 |
|        | 8 × 5      | 1.4201  | 0.0290  | 0.0290  | 0.0290 | 97.091 |
|        | 8 × 3      | 2.9514  | 0.0172  | 0.0169  | 0.0171 | 98.273 |
|        | 8 × 8      | 4.8022  | 0.0182  | 0.0182  | 0.0182 | 98.182 |

overcome this increase in data, the use of the dimensional reduction method is the solution. The choice of KPCA dimension reduction method emphasizes more on the variation between the data used (Casia, IITD-India, and PolyU) so that the different background color between the data is not the main problem. This non-uniformity can be assumed as a non-linear data. The KPCA dimension reduction method emphasizes the choice of a kernel center-kernel. In the research conducted, the KPCA method uses training, evaluating, and testing data for three images for each data input. The size and number of output images from the Gabor process are $I_G = [16 \times 16 \times \varphi \times \kappa; i \times j]$ with $I_G$ is Gabor’s image, $\varphi$ orientation variable, $\kappa$ scale parameter, $i$ number of image data input, and $j = 3$ is the choice for image variation used for training data. If the test uses 5 sample size images $[128 \times 128]$, there will be 30 number of one column images of $[16 \times 16 \times 8 \times 5; 3 \times 5] = [10240 \times 15]$. The output of testing data is obtained through the diagonal of the SVD process which has a large image $[15 \times 15]$. The final output of KPCA is the transfer multiplication of training data with testing dimensions $[15 \times 10240 \times 10240 \times 15] = [15 \times 15]$. Finally, in the last research, the cosine method is used to compare impostor data with genuine data generated from the testing and evaluating information patterns. The effect of using covar or contra-variance values has an impact on the output of the cosine system. The covar value in the study was obtained from comparative data that is training as much as $i$ sample multiplied...
**Figure 2:** The CMC curve (the cumulative match curve) that also used to view the optimization system through several draws of line with the $x$–axis to a constant value of Rank and the $y$–axis for the recognition rate. The curve has the opposite view with the ROC curve; getting down and then move the far right side is the best system. Some dimension reduction is used to represent the Gabor methods: (a) KPCA, (b) PCA, (c) KFA, and (d) LDA.

**Figure 3:** The DET curve (detection error tradeoff) which describes the performance of the system by splitting vertically in the middle of the figure with $x$–axes for the false alarm probability and $y$–axis for the miss probability. A smaller value in $x$–axis is the better method. In the figure depict the behavior of alteration variable in Gabor technique for the environment of (a) KPCA, (b) PCA, (d) KFA, and (d) LDA.
Figure 4: The EPC curve (the expected performance curve) is also used to clarify the electoral performance of the system which generally lies of the lines very close horizontally splitting the curve with $x-$axis for the Alpha variable and $y-$axis for the error rate. The smaller value of $y-$axis is the better system where it is visible clearly that the line with cyan color represent the Gabor parameter $\varphi = 8$ and $\kappa = 5$ dominated for three-part from the four section method: (a) KPCA, (b) PCA, (c) KFA, and (d) LDA.

by three variations with the form of $inv$ equation ($\text{cov(train(1:n;?:))}$). The values of $x$ and $y$ are impostor and genuine values both data from testing and evaluating. Value 3 is used because in the study using the number of variations in the image of each as many as three images. After the cosine matching process is complete, system results are obtained in the form of numerical values in the tabulation and the appearance of four biometric performance curves, namely: ROC (receiver operating characteristic), EPC (expected performance curves), DET (detection error trade-off), and CMC (cumulative match-score curves).

4. Conclusions
By using seven different parameters of orientation and scale, the Gabor method is obtained the results that $8 \times 5$ is the best option for verification and identification of palmprint recognition. The results of the study will produce the maximum value when performing the image filter process in the image enhancement process before the Gabor process is completed. In this study, the filter used is by using the wavelet technique followed by the skeleton method. Results from the research showed the KPCA is leading as a dimension reduction tool compared with KFA, LDA, and PCA method. From the three databases used, the KPCA superior in terms of both speed processing time and high-performance rate. When using the PolyU database which has the most significant number of an object inside, the time-consuming process is 0.74964s with EER value is 0.00835, and the level accuracy of verification is about 99.182%.

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