

## Palmprint recognition system using VR-LBP and KAZE features for better recognition accuracy

Noor Aldeen A. Khalid<sup>1</sup>, Muhammad Imran Ahmad<sup>2,6</sup>, Tan Shie Chow<sup>2</sup>, Thulfiqar Hussein Mandeel<sup>3</sup>, Ibrahim Majid Mohammed<sup>4</sup>, Mokhalad Abdulameer Kadhim Alsaedi<sup>5</sup>

<sup>1</sup>Department of Medical Instruments Engineering Techniques, Bilad Alrafidain University College, Diyala, Iraq

<sup>2</sup>Faculty of Electronic Engineering and Technology, Universiti Malaysia Perlis, Arau, Malaysia

<sup>3</sup>Department of Computer Techniques Engineering, College of Information Technology, Imam Ja'afar Al-Sadiq University, Samawah, Iraq

<sup>4</sup>School of Electrical and Electronic Engineering, Universiti Sains Malaysia, Pulau Pinang, Malaysia

<sup>5</sup>Department of Computer Engineering Techniques, Bilad Alrafidain University Collage, Diyala, Iraq

<sup>6</sup>Institute of Sustainable Agrotechnology, Universiti Malaysia Perlis, Arau, Malaysia

### Article Info

#### Article history:

Received Sep 9, 2022

Revised Aug 1, 2023

Accepted Oct 22, 2023

#### Keywords:

Euclidean distance

Palmprint recognition

Principal component analysis

Vertical-local binary patterns

KAZE

### ABSTRACT

The palmprint recognition system has gained significant attention in security and law enforcement due to its unique features, such as principle lines, ridges, and wrinkles. However, many existing methods for extracting these features have limited accuracy, especially when the image illumination varies or the size of the processed pixels increases. Previous studies have shown that the local binary patterns (LBP) algorithm is effective for palmprint recognition due to the rich texture characteristics of a palmprint. In this paper, we propose a new technique for a robust contact-based palmprint identification system using vertical-LBP and KAZE feature detection. Our technique aims to improve recognition accuracy by using KAZE, which is a nonlinear diffusion approach that extracts nonlinear features from the evolution of the illuminance of an image. We also utilize principal component analysis (PCA) to reduce the dimensionality of the generated descriptor vector elements. The proposed method was tested on the PolyU database and achieved recognition accuracy of 99.7%.

This is an open access article under the [CC BY-SA](#) license.



### Corresponding Author:

Noor Aldeen A. Khalid

Department of Medical Instruments Techniques Engineering, Bilad Alrafidain University College

Diyala 32001, Iraq

Email: nooraldeen4561@gmail.com

## 1. INTRODUCTION

Palmprint recognition is considered the most efficient technique of biometric recognition, with the advantages of low cost, low-resolution, non-intrusion, reliability, and high performance in the field of biometric recognition [1], [2]. There are two types of palmprint images: high-resolution and low-resolution. Each type is appropriate for specific applications; for example, forensic applications usually use high-resolution images, while low-resolution images are used for access controls [3].

Since Shu and Zhang [4] first proposed it, palmprint has piqued the interest of numerous researchers numerous methodologies have been introduced and expanded for palmprint recognition [5] which are primarily based on: texture, principal lines, and subspace. The proposed method primarily focuses on designing texture-based local binary pattern (LBP) due to its reliability. LBP which has been proposed by Ojala *et al.* [6] gathers momentum in the research area of palmprint recognition and several LBP variants have been proposed. These variants include local ternary pattern (LTP), dominant local binary pattern

(DLBP), center-symmetric local binary pattern (CS-LBP), local derivative pattern (LDP), and completed local binary pattern (CLBP) [5].

Sehgal [7] proposed a palmprint recognition system using LBP and support vector machines (SVM), while Tamrakar and Khanna [8] presented an approach to palmprint identification based on local uniform LBP (ULBP) distribution. ULBP applies to the pattern with minimal discontinuities of uniform appearance. Tarhouni *et al.* [9] proposed a feature extraction technique using a pyramid-oriented gradient histogram with LBP, where the characteristics for the classification of palmprints are concatenated, while multi-resolution capabilities could represent more image features in different settings. Guo *et al.* [10] proposed a collaborative representation model with hierarchical multi-scale LBP (HMS-LBP) for palmprint recognition. HMS-LBP can obtain useful information from non-uniform patterns as well as from the grayscale, rotation, and illumination effects. Dubey and Kanumuri [11] an orientation diagram was extracted using anisotropic filters (AF) from an optimal local binary directional pattern (OLdirBP). The characteristics were finally achieved using local directional patterns accompanied by LBP. Dubey *et al.* [12] proposed the ability of the binary wavelet transform (BWT) to discriminate against palmprints. Further, micro and macro-pattern histograms are extracted using local binary pattern (LBP) from different transformed bit planes and concatenated to form the feature vector. Several recent studies [13], [14] have suggested combining hierarchical multi-scale complete local binary pattern (HMS-CLBP) and weighted sparse representation-based classification (WSRC). However, basic LBP it is not rotation invariant, meaning that the LBP features will change if the image is rotated. This can be addressed by using extended LBP or by using vertical local binary patterns (VR-LBP), in combination with other descriptors that are rotation invariant.

Attallah [15] proposed a novel approach for the palmprint fusion of multiple features. These features are provided from multi-spectral images at 940 nm, which allow the extraction of the information under the skin of the palm. In this context, CLBP, which added an extra bit for each bit encoded by LBP corresponding to a neighbor of the local neighborhood, was used to construct a robust feature descriptor that exploits both the sign and the inclination information of the differences between the center and the neighbor grey values.

There are many methods for local feature detection, and the most common are speeded-up robust features (SURF) [16], scale-invariant feature transform (SIFT) [17], and oriented fast and rotated brief (ORB) [18]. They detect and define features at different scale levels by constructing or approximating the image's Gaussian scale space. Moreover, the Gaussian blur violates the natural limits of images and smooths all information with noise to the same point, decreasing the precision and distinctiveness of the localization [19].

Alcantarilla *et al.* [20] introduced the KAZE feature, which is a wind-meaning to extract features with higher discrimination power; the wind is characterized in nature as a large-scale flow of air, and thus this flow is usually regulated by nonlinear processes. The KAZE feature detects and describes 2D features in nonlinear scale space using nonlinear diffusion filtering. The KAZE adjusted blurring locally to the images, reducing noise while maintaining object borders, achieving superior precision and distinct positioning. Figure 1 illustrates the four steps of the classic method for palmprint recognition: getting an image, preprocessing it, feature extraction, and matching.



Figure 1. Palmprint recognition system

The main contribution of this paper is proposing a new technique that combines VR-LBP and KAZE features, which further improves the accuracy of recognition by generating higher knowledge of discrimination during the extraction of the features by using PolyU database contact palmprint images. Among the many emerging techniques for palmprint recognition, the high recognition levels produced by various palmprint image texture feature extraction methods are the most common. The following is the structure of this paper: section 2 describes the method, section 3 highlights the results and discussion of the experiment, and section 4 is the conclusions.

## 2. METHOD

The palm has texture features, and to extract these features, the algorithm must be modified to extract more features from the palm. In the proposed method, the way to compare the neighbors with the center pixel of VR-LBP is changed to a vertical one rather than the default one; however, the grayscale palmprint image is typically a texture image that primarily consists of ridges and principal lines. By using VR-LBP, it will ensure recognition accuracy by having many more features than the basic LBP, as shown in Figure 2.

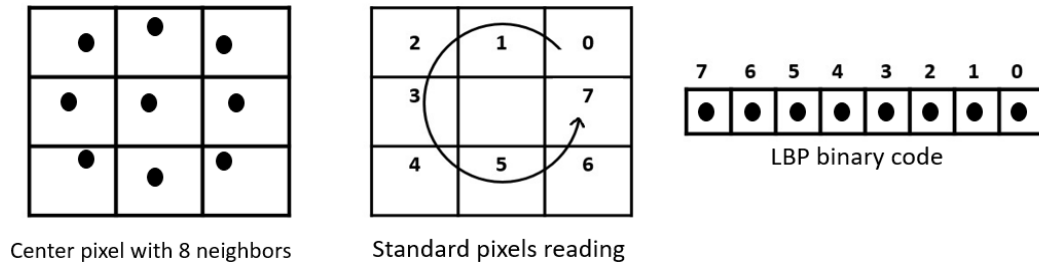


Figure 2. The basic operator of LBP

Here is the difference between VR-LBP and the original one: by comparing the central pixel with its neighbors in a vertical way, the value of the central pixel will be different, as shown in Figure 3, where 0-7 are the sequences of neighbors in a vertical way using (1).

$$LBP_{p,R} = \sum_{p=0}^{p-1} s(g_p - g_c) 2^p \quad (1)$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

Where  $g_c$  is gray value of a central pixel,  $g_p$  is the value of neighbors,  $P$  is the total number of involved neighbors,  $R$  is the radius of the neighbors, and  $g_p$  is  $(R \cos(2\pi p/P), R \sin(2\pi p/P))$ , Figure 4 shows the basic LBP vs VR-LBP, where Figure 4(a) is the original palm image, Figure 4(b) applying LBP and Figure 4(c) applying VR-LBP.

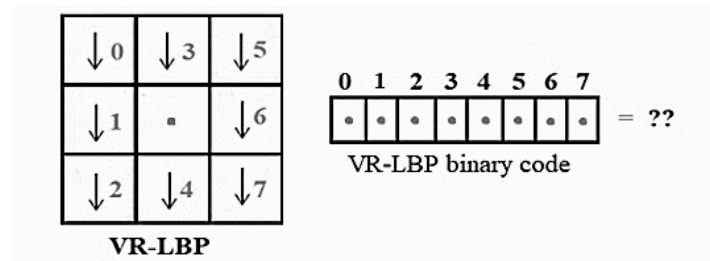


Figure 3. The procedure of VR-LBP

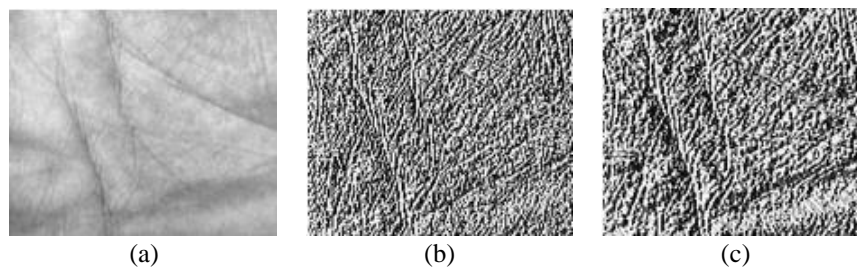


Figure 4. The different between LBP vs VR-LBP; (a) original palm image, (b) basic LBP, and (c) VR-LBP

To promote recognition accuracy, our method is applied, and it can be summarised in four steps, which are: i) the final function code is derived from VR-LBP, while the number of neighbors for VR-LBP that has been used is 3x3, ii) extract the features by using KAZE feature detection in different parameters, iii) apply PCA for dimension reduction, which is proposed in [21], and iv) finally, the produced features are matched using euclidean distance. Figure 5 depicts the proposed method's flow chart, and Figure 6 depicts an example of using VR-LBP.

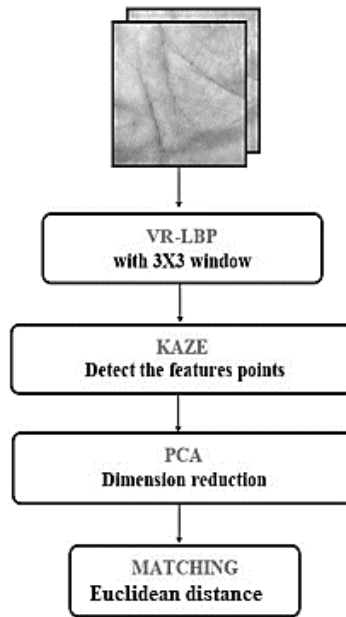


Figure 5. Proposed method flow

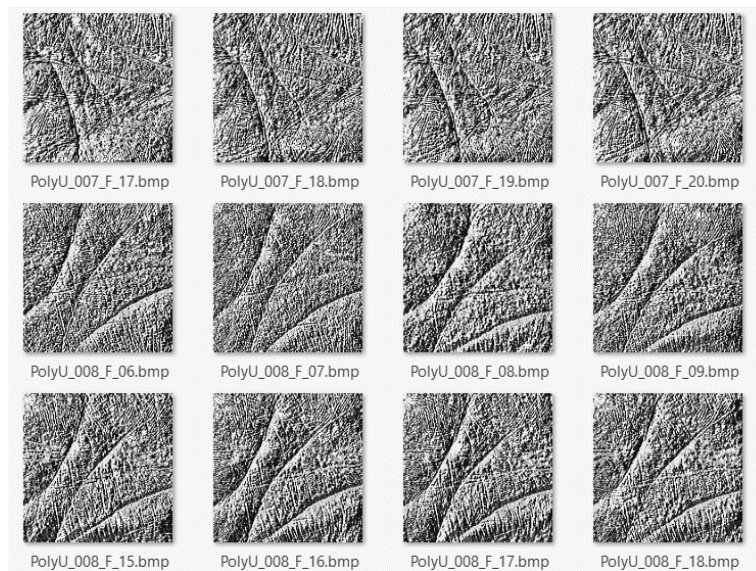


Figure 6. Samples of VR-LBP

Following the implementation of VR-LBP, the following steps are taken to detect the KAZE feature: first, build an additive operator splitting (AOS) input image non-linear scale space and variable conductivity diffusion system. Second, the calculation of the scale-normalized Hessian matrix in the nonlinear scale space. Third, detect the 2D feature points in the special Hessian matrix by measuring the local limit of 3x3 neighborhoods; last but not least, calculate the feature points and obtain an invariant scale and rotation descriptor dependent on the image derivatives of the first order [22], [23] nonlinear diffusion as (3):

$$\frac{\partial L}{\partial t} = \text{div}(c(x,y,t) \cdot \nabla L) \quad (3)$$

where  $\nabla$  and  $\text{div}$  are respectively the divergence and gradient operators and  $c$  is the conductivity function of the diffusion equation, time ( $t$ ) is the scale parameter, and larger values lead to simpler image representations.

$$c(x,y,t) = g(|\nabla L_\partial(x,y,t)|) \quad (4)$$

The  $\nabla L\sigma$  is the gradient of a gaussian smoothed version of the original image  $L$ . Perona and Malik described two different formulations for the conductivity function  $g$ :

$$g1 = \exp\left(-\frac{|\nabla L\sigma|^2}{k^2}\right), g2 = 1/1 + \frac{|\nabla L\sigma|^2}{k^2} \quad (5)$$

where  $k$  is the contrast factor regulating the diffusion level. The  $g1$  feature encourages edges of high contrast, while  $g2$  encourages large and smaller regions [20]. Additive operator splitting (AOS) formulation:

$$\frac{L^{i+1}-L^i}{T} = \sum_{l=1}^m A_l (L^i) L^{i+1} \quad (6)$$

where  $A_l$  is a matrix encoding each dimension's image conductivity. The solution  $L^{i+1}$  can be obtained as (7):

$$L^{i+1} = (1 - T \sum_{l=1}^m A_l (L^i))^{-1} L^i \quad (7)$$

For detecting points of interest:

$$L_{\text{Hessian}} = \partial^2 (L_{xx} L_{yy} - L_{xy}^2) \quad (8)$$

where  $(L_{xx}, L_{yy})$  are the horizontal and vertical derivatives of the second order, and where  $L_{xy}$  is the cross derivative of the second order. Due to the set of filtered images from  $L^i$  nonlinear space. The keypoints location is determined using the proposed in [23] sub-pixel accuracy.

For the dimension reduction using linear projection based on the Karhunen–Loeve approach, the PCA technique reduces the dimensionality of palmprint data. This approach maximizes the distribution of all the predicted image samples of palmprint. Dimensional feature reduction increases the power of discrimination and reduces the time and memory cost of computing. In the PCA algorithm, the linear projection approach is used to project high-dimensional data into a low-dimensional subspace [24].

Consider a collection of sample palmprint images  $\{y_1, y_2, y_n\}$  collected image space to illustrate the computation of main components, and assume that each palmprint image belongs to a different class of classes  $\{x_1, x_2, x_c\}$ . Consider the linear transformation that transforms the original high-dimensional palmprint image space with  $n$ -dimensions into a new  $m$ -dimensional low-dimensional feature space where  $m \ll n$  obtained from (9) which is the linear transformation equation, may represent the generated feature vectors  $y^k \in \mathbb{R}^m$ .

$$y_k = W^T y_k \quad (9)$$

where  $k=1,2, N$ , (10) represents the entire Scatter matrix  $S_T$ .

$$S_T = \sum_{k=1}^N (y_k - \mu)(y_k - \mu)^T \quad (10)$$

where  $N$  is the total sample of palmprint images and  $\mu \in \mathbb{R}^m$  which is the mean vector of all palmprint images,  $W^T S_T W$  is the output of  $y_k$  by linear transition with  $W^T$ .  $T$  optimizing the scatter matrix determinant obtained from the projected image of the palmprint, and projection  $W_{\text{opt}}$  is chosen to maximize the determinant of the expected sample total scatter matrix, i.e.:

$$W_{\text{opt}} = \text{argmax} |W^T S_T W| = [w_1 w_2 \dots w_m] \quad (11)$$

where  $[w_1 w_2 \dots w_m]$  represents the eigenvectors with  $n$ -dimensions from which they are chosen based on their own corresponding largest values.

$$Z(m) = T(m) - \bar{X} \quad (12)$$

where  $Z$  is the 2D zero-mean training data matrix,  $(\bar{X})$  is the mean row vector of the training data matrix,  $(m)$  is the average palmprint image vector of a given subject's training palmprint, and  $T$  is the amount of the variable. For eigenvalues and eigenvectors from the covariance matrix using as (13):

$$S = \frac{1}{n} \sum_{i=1}^n (x_i)(x_i)^T \quad (13)$$

where  $S$  is the 2D covariance matrix,  $x$  is the zero-mean 2D training data matrix, and  $x^T$  is the zero-mean 2D training data matrix transposing matrix. Formula for measuring the eigenvectors and eigenvalues is as (14):

$$S.e = \lambda.e \quad (14)$$

where  $S$  is the 2D matrix,  $e$  is the eigenvector matrix, and  $\lambda$  is diagonal matrix of the eigenvalue.

$$F = Z * e_{\text{projected}} \quad (15)$$

Where  $e_{\text{projected}}$  is the eigenvector after projection and  $F$  is the feature matrix of training data,  $Z$  is the zero mean data matrix. At the last step for matching, the euclidean distance classifier, to calculates the distance between features in the template and recognition according to the smallest distances. In a cartesian coordinate system, assume that  $q=(q_1, q_2, q_n)$  and  $p=(p_1, p_2, p_n)$  are two points in the euclidean  $n$ -space. Then, by using the Pythagorean (16) [25], the example of the euclidean distance between two points is shown in Figure 7.

$$ED(p,q) = \sqrt{\sum_i^n (p_i - q_i)^2} \quad (16)$$

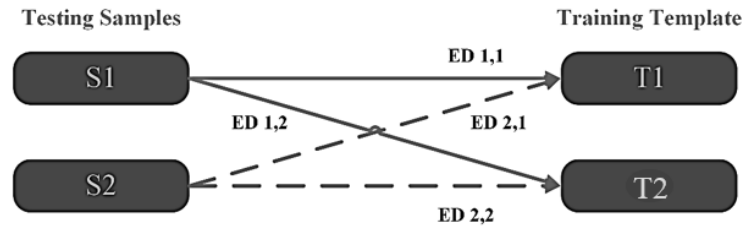


Figure 7. Euclidean distance

### 3. RESULTS AND DISCUSSION

In this section, we have developed a new technique for a robust palmprint identification system using VR-LBP and KAZE feature detection. The PolyU database has been used to validate our proposed method's efficiency and compare it with other palmprint recognition algorithms. The database includes 7,752 palmprint images with a size of 384\*286 from 386 palms. Palmprint images have been collated in two different sessions, containing more than nine images. Two sessions have an average duration of two months, introducing improvements in light conditions, emphasis on the imaging system, and skin texture deformation due to various hand positions between the two image capture occasions.

Assumedly, accuracy is one of the most important considerations to be considered. Thus, in this segment, most analyses concentrate on accuracy rather than other factors, even though, during the comparison, our methods were compared with those of other works. In these experiments, an evaluation protocol has been used, like nearest feature detection according to our detection method (KAZE), and compared with SURF based on the number of feature points as shown in Table 1. From the Table 1, KAZE feature detection is better than SURF in terms of detection points at the default parameters, which can help ensure recognition accuracy according to the increasing number of features.

In this work, the sharp edge was chosen according to the number of points that can be seen in Table 2. Nevertheless, in the VR-LBP, the number of points is increasing, which means it's improved and will improve the accuracy during the matching process. There are several parameters to be defined in the proposed algorithm that will affect the recognition rate, such as the diffusion value, the sub-image dimension, the value of  $\lambda$ , and the PCA dimensions. In this part of the experiment, all classes (386 palms) are used; for each palm, 8 samples are used as training samples, and 1 sample for each class is used as a testing sample.

Table 1. Comparison of KAZE and SURF

	SURF (points)	KAZE (points)
Original image	0	610
VR-LBP	276	634
Basic LBP	257	628

Table 2. Comparison KAZE with changing the value of diffusion

KAZE parameters	Original image (points)	VR-LBP (points)	Basic LBP (points)
Edge	198	631	628
Region	610	634	628
Sharp-edge	203	657	632

In Table 3, could notice the accuracy increasing while the number of classes and the number of images increased according to the PCA algorithm and with the improvement of VR-LBP+KAZE. From Table 4, using basic LBP and PCA, the accuracy is less without KAZE compared to our proposed method, and from Table 5, it appears that the method of Zhang [1] and El-Tarhouni [9], from Table 4, using basic LBP and PCA, the accuracy is less without KAZE compared to our proposed method, and from Table 5, it appears that the method of Zhang [1] and El-Tarhouni [9], is less accurate since the number of classes that

have been used is not that much the same as our proposed method; nevertheless, increasing the number of neighbors will lead to an increase in time and computation complexity. In the Tables 3 and 4 can see the accuracy increasing as the number of classes and images increases. This is due to the PCA algorithm and the improvement of VR-LBP+KAZE. The fact that the accuracy is lower than that of VR-LBP demonstrates that the proposed method is effective. Figure 8 depicts the accuracy of the basic LBP and VR-LBP when KAZE and PCA are used. The experiment was carried out with MATLAB 2018b installed on a computer with a Windows 10 platform, a CPU core i78565U, 8 GB of RAM, and 533 MB/s read and 442 MB/s write speed solid-state drive (SSD) memory.

Table 3. VR- LBP with KAZE sharp-edge diffusion  
+ PCA using euclidean distance

Class number	Number of train image	Accuracy (%)
386	2	76.16
	3	84.19
	4	90.67
	5	94.81
	6	97.68
	7	98.44
	8	99.7

Table 4. Basic LBP+KAZE + PCA

Class number	Number of train image	Accuracy (%)
386	2	66.7
	3	72.9
	4	83.5
	5	87.9
	6	91.34
	7	91.6
	8	93.6

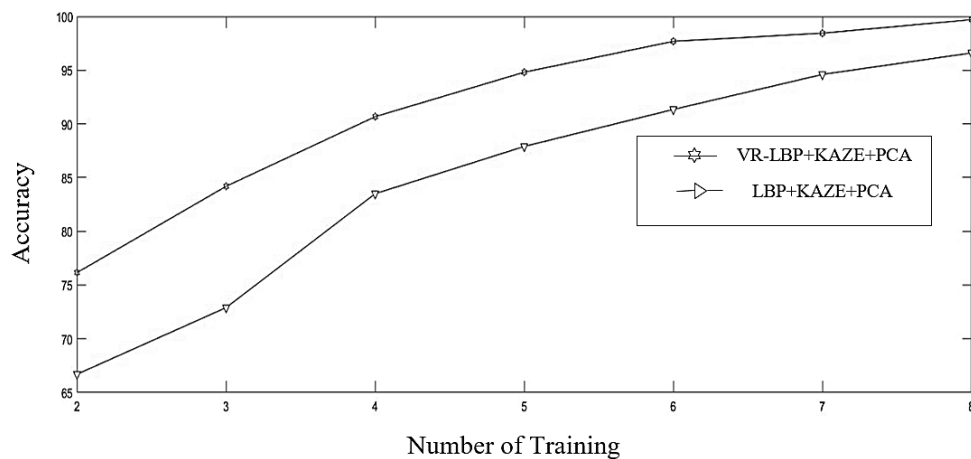


Figure 8. Accuracy graph between two methods

Table 5. Comparison of previous work

Method	Number of class	Accuracy (%)
[1]	129	98.06
[9]	250	99.27
Our proposed	386	99.7

#### 4. CONCLUSION

To avoid computation complexity, the discrimination capability of the image is used in this work for a robust palmprint identification system using VR-LBP with several neighbors (3\*3). The system performs faster compared with the different number of neighbors, VR-LBP which made the palm features more apparent than basic LBP which leads to an increase in the recognition accuracy, nevertheless, KAZE feature detection used nonlinear diffusion approaches for detecting the palm features which confirmed the result when compared with other methods, last but not least use PCA for reducing the dimensionality of the generated descriptor vector elements. The proposed method was tested on the PolyU database and successfully improved the recognition accuracy, resulting in a high percentage of 99.74%.

#### ACKNOWLEDGEMENT





This work is supported by Grants from Fundamental Research Grant Scheme of Ministry of Higher Education Malaysia (FRGS/1/2021/ICT02/UNIMAP/03/1).

## REFERENCES




- [1] S. Zhang, H. Wang, W. Huang, and C. Zhang, "Combining Modified LBP and Weighted SRC for Palmprint Recognition," *Signal, Image and Video Processing*, vol. 12, no. 6, pp. 1035–1042, Sep. 2018, doi: 10.1007/s11760-018-1246-4.
- [2] M. Farmanbar and Ö. Toygar, "Spoof detection on face and palmprint biometrics," *Signal, Image and Video Processing*, vol. 11, no. 7, pp. 1253–1260, 2017, doi: 10.1007/s11760-017-1082-y.
- [3] M. M. H. Ali, A. T. Gaikwad, and P. Yannawar, "An approach to improve Palmprint Recognition Accuracy by Using Different Region of Interest Methods with Local Binary Pattern Techniques," *Indian Journal of Science and Technology*, vol. 11, no. 22, pp. 1–12, 2018, doi: 10.17485/ijst/2018/v11i22/122752.
- [4] W. Shu and D. Zhang, "Palmprint verification: an implementation of biometric technology," pp. 219–221, 2002, doi: 10.1109/icpr.1998.711120.
- [5] C. Liu, D. Zhong, and H. Shao, "Data Protection in Palmprint Recognition via Dynamic Random Invisible Watermark Embedding," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 10, pp. 6927–6940, 2022, doi: 10.1109/TCSVT.2022.3174582.
- [6] T. Ojala, M. Pietikainen, and T. Maenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, Jul. 2002, doi: 10.1109/TPAMI.2002.1017623.
- [7] P. Sehgal, "Palm recognition using LBP and SVM," *Int. J. Inf. Technol. Syst.*, vol. 4, no. 1, pp. 35–41, 2015.
- [8] D. Tamrakar and P. Khanna, "Occlusion Invariant Palmprint Recognition with ULBP Histograms," *Procedia Computer Science*, vol. 54, pp. 491–500, 2015, doi: 10.1016/j.procs.2015.06.056.
- [9] W. El-Tarhoui, L. Boubchir, M. Elbendak, and A. Bouridane, "Multispectral palmprint recognition using Pascal coefficients-based LBP and PHOG descriptors with random sampling," *Neural Computing and Applications*, vol. 31, no. 2, pp. 593–603, 2019, doi: 10.1007/s00521-017-3092-7.
- [10] X. Guo, W. Zhou, and Y. Zhang, "Collaborative representation with HM-LBP features for palmprint recognition," *Machine Vision and Applications*, vol. 28, no. 3–4, pp. 283–291, 2017, doi: 10.1007/s00138-017-0821-y.
- [11] P. Dubey and T. Kanumuri, "Optimal local direction binary pattern based palmprint recognition," *2015 International Conference on Computing for Sustainable Global Development, INDIACom 2015*, pp. 1979–1984, 2015.
- [12] P. Dubey, T. Kanumuri, and R. Vyas, "Palmprint recognition using binary wavelet transform and LBP representation," *International Conference on Recent Innovations in Signal Processing and Embedded Systems, RISE 2017*, vol. 2018-Janua, pp. 201–205, 2018, doi: 10.1109/RISE.2017.8378154.
- [13] S. Zhang, H. Wang, and W. Huang, "Palmprint identification combining hierarchical multi-scale complete LBP and weighted SRC," *Soft Computing*, vol. 24, no. 6, pp. 4041–4053, 2020, doi: 10.1007/s00500-019-04172-3.
- [14] A. Amraoui, Y. Fakhri, and M. A. Kerroum, "Multispectral Palmprint Recognition based on Fusion of Local Features," *International Conference on Multimedia Computing and Systems -Proceedings*, vol. 2018-May, 2018, doi: 10.1109/ICMCS.2018.8525989.
- [15] B. Attallah, A. Serir, and Y. Chahir, "Feature extraction in palmprint recognition using spiral of moment skewness and kurtosis algorithm," *Pattern Analysis and Applications*, vol. 22, no. 3, pp. 1197–1205, 2019, doi: 10.1007/s10044-018-0712-5.
- [16] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Speeded-Up Robust Features (SURF)," *Computer Vision and Image Understanding*, vol. 110, pp. 346–359, 2008.
- [17] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *International journal of computer vision*, vol. 60, no. 2, pp. 91–110, 2004.
- [18] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, "ORB: An efficient alternative to SIFT or SURF," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2564–2571, 2011, doi: 10.1109/ICCV.2011.6126544.
- [19] X. Liu, Y. Wang, J. Du, S. Liao, J. Lou, and B. Zou, "Robust hybrid image watermarking scheme based on KAZE features and IWT-SVD," *Multimedia Tools and Applications*, vol. 78, no. 5, pp. 6355–6384, 2019, doi: 10.1007/s11042-018-6361-2.
- [20] P. F. Alcantarilla, A. Bartoli, and A. J. Davison, "KAZE Features," no. May, 2014, doi: 10.1007/978-3-642-33783-3.
- [21] S. Wold, K. Esbensen, and P. Geladi, "Principal component analysis," *Chemom. Intell. Lab. Syst.*, vol. 3, no. 37–52, p. 1987, 1987, doi: 10.1039/c3ay41907j.
- [22] N. A. A. Khalid, M. I. Ahmad, T. H. Mandeel, and M. N. M. Isa, "Palmprint features matching based on KAZE feature detection," *Journal of Physics: Conference Series*, vol. 1878, no. 1, 2021, doi: 10.1088/1742-6596/1878/1/012055.
- [23] M. Brown and D. Lowe, "Invariant Features from Interest Point Groups," pp. 23.1–23.10, 2013, doi: 10.5244/c.16.23.
- [24] T. H. Mandeel, M. I. Ahmad, M. N. Md Isa, and R. Ngadiran, "Palmprint recognition using principle component analysis implemented on TMS320C6713 DSP processor," *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 8, no. 4, pp. 41–46, 2016.
- [25] J. Malik, "Investigations on Feature Extractions and Matching for Palmprint Based Biometric," 2018.

## BIOGRAPHIES OF AUTHORS






**Noor Aldeen A. Khalid**     received his Ph.D. in Computer Engineering from Universiti Malaysia Perlis (UniMAP), School of Computer and Communication Engineering since in 2022. Studied his M.Sc. at UniMAP, Malaysia, from 2016 until 2017. He is a senior lecturer at Department of Medical Instruments Techniques Engineering, Bilad Alrafidain University College. His main research interests are pattern recognition and image processing. He can be contacted at email: nooraldeen4561@gmail.com and dr.nooraldeen@bauc14.edu.iq.






**Muhammad Imran Ahmad**    received his Ph.D. in Computer Engineering from Newcastle University, the United Kingdom in 2014. Currently, he is a senior lecturer at the School of Computer and Communication Engineering, Universiti Malaysia Perlis. His research interests include biometrics, signal analysis, and image processing. He can be contacted at email: m.imran@unimap.edu.my.






**Tan Shie Chow**    received his B. Eng degree in computer engineering from University Malaysia Perlis in 2022. He is currently pursuing a master's degree in computer engineering with Universiti Malaysia Perlis. His research interests are image processing. He can be contacted at email: orience97@gmail.com.






**Thulfiqar Hussein Mandeel**    received his Ph.D. Computer Engineering from Universiti Malaysia Perlis (UniMAP), Malaysia in 2018. Studied his M.Sc. at UniMAP, Malaysia, from 2014 until 2015. he is a senior lecturer at the College of Information Technology, Imam Ja'afar Al-Sadiq University, Iraq. His main research interests are pattern recognition and image processing. He can be contacted at email: thulfiqarhussein@gmail.com.



**Ibrahim Majid Mohammed**    received a B.Eng. degree in computer and communication engineering from Al-Rafidain University College, Baghdad, Iraq, in 2016, and a master's degree in computer and communication engineering from Universiti Malaysia Perlis in 2020. He is currently pursuing a Ph.D. degree in electrical and electronic engineering with Universiti Sains Malaysia (USM), Penang, Malaysia. His research interests are pattern recognition and image processing. He can be contacted at email: eng.ibraheem.m.94@gmail.com.



**Mokhalad Abdulameer Kadhim Alsaeedi**    received his Ph.D. in Electrical and Computer Engineering from Altinbas University, School of Computer Engineering since in 2022. Studied his M.Sc. at Altinbas University from 2017 until 2019. He is a senior lecturer at Department of Computer Engineering Techniques, at Bilad Alrafidain University College. His main research interests are machine learning and image processing. He can be contacted at email: khaldoon@bauc14.edu.iq.