INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2025, VOL. 71, NO. 2, PP. 555–559
Manuscript received February 28, 2025; revised May, 2025. doi: 10.24425/ijet.2025.153604

Identifying three-dimensional palmprints with Modified Four-Patch Local Binary Pattern (MFPLBP)

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***Abstract*—Palmprint biometrics is the best method of identifying an individual with a unique palmprint for every person. The present paper formulates a new methodology towards the identification of 3D palmprints using the Modified Four-Patch Local Binary Pattern (MFPLBP). It improves upon the conventional Four-Patch Local Binary Pattern (FPLBP) by integrating the adaptive weight with the improved texture extraction. Both approaches are created to support the intricate surface information of 3D palmprints. The MFPLBP can exactly capture local variations and is noise and illumination invariant. There are extensive experiments done in this paper and establish that MFPLBP outperforms traditional LBP methods and other state-of-the-art methods in recognition rates. The experiments establish that MFPLBP is a efficient and effective method of making use of 3D palmprints in real-world biometric verification.**

***Keywords*—Palmprint identification, Biometrics, Four-Patch Local Binary Pattern, PolyU 3D Palmprint Database**

I. Introduction

PALMPRINT biometrics is valuable and reliable for identification because of the unique patterns of the palmar surface. While traditional systems often struggle with challenges like varying lighting conditions and poses, 3D palmprint recognition provides more precise feature representation, overcoming these limitations [1], [2].

The study in [1] introduces a Collaborative Representation (CR)-based framework for 3D palmprint recognition, focusing on l1-norm and l2-norm regularizations. This approach includes a block-wise, statistics-based feature extraction technique, dividing the 3D palmprint into homogeneous blocks and generating surface-type histograms for each block. Evaluations using the PolyU 2D-3D database showed excellent recognition accuracy.

Similarly, [2] presents an innovative 3D palmprint recognition method that combines Principal Component Analysis (PCA) with Blocked Surface Type (ST) features. This technique improves one-to-many identification speeds and reduces the issues caused by small sample sizes. It integrates a nearest-neighbor classifier, enhancing the method's scalability and efficiency, ensuring quick and accurate discrimination with minimal computational load.

In [3], the Precision Direction Code and Compact Surface Type (PDCST) technique is introduced for 3D palmprint representation. This method combines 2D texture-based information (captured by PDC) and 3D surface features (emphasized by CST) to create a unified descriptor. A two-phase sparse representation technique is used for feature identification, and experimental results underline the method's strong potential for real-world applications.

Another approach, as shown in [4], focuses on a system that fuses both 2D and 3D palmprint modalities at the matching score level. The 3D palmprint is converted to grayscale images by mean curvature and Gauss curvature, and therefore this approach facilitates simple integration, leading to enhanced recognition performance.

The research in [5] has employed both 2D and 3D palmprint features in a personal identification system. Referring to the technique based on methods differing with regard to active stereo methods and surface curvature, the recognition is improved in terms of accuracy using a highly secure system to make it hard to fake.

In [6], presents a 3D palmprint authentication system with the help of structured light illumination. It fuses identification and verification experiments at the score-level. A fast feature matching scheme is used to build an effective and stable solution. Meanwhile, [7] suggests an online personal authentication solution using low-resolution images and palmprint technology. Both a dedicated imaging device and an optimized recognition algorithm make it an effective solution for practical usage.

The research in [8] designs a 2D and 3D palmprint-based multibiometric system using techniques such as Log-likelihood scores, Hidden Markov Models (HMMs), and PCA for accurate identification. The system is established to be robust with very high accuracy on the PolyU 2D-3D database.

For facial expression recognition, Local Directional Number Pattern (LDN) scheme presented in [9] is highlighted. LDN encodes significant direction indices, generating discriminative codes that capture directional features in face texture. The method's reliability is confirmed across various conditions.

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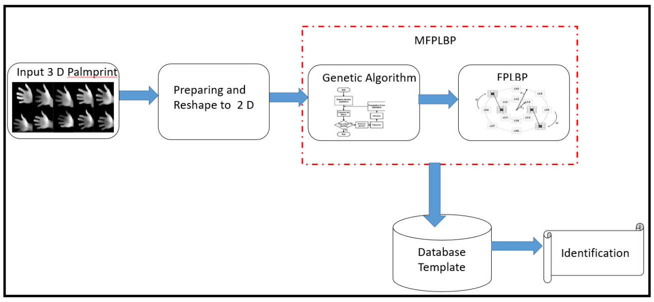

Fig. 1. The suggested palmprint identification technique

In [10], the LDN method for facial analysis is further expanded, using direction indices and compass masks to represent structural patterns in face textures. The system generates consistent feature vectors despite variations in lighting, emotions, and noise.

The approach in [11] enhances facial recognition by utilizing LDN patterns with compass masking. This method yields distinctive codes for recognizing facial expressions, showing its versatility across different facial analysis tasks. In [12], the LTDF-based modified LDN (LTDFMLDN) descriptor is introduced, outperforming existing techniques for texture recognition in facial datasets.

Other works, such as [13], explore further extension of the LDN pattern towards face recognition depending on salient direction indices with the aim to describe local patterns. Consistent results are produced irrespective of changing environments. Similarly, [14] examines the Local Directional Range Pattern (LDRN) to be a very discriminative face feature descriptor.

In addition to palmprint biometrics, [15] describes the Finger Outer Knuckle (FOK) as an efficacious and secure biometric, which uses LDN codes from gradient-based compass masks to obtain features. Performance is demonstrated using the IIT Delhi Finger Knuckle database.

For face recognition systems, [16] combines Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and LDN for training and classification. Experiments on the JAFFE and IFD databases confirm the robust performance of the system.

Finally, the research in [17] compares similarity learning methods in face recognition and suggests that descriptor-based approaches are more effective in multiple-choice identification contexts, with the addition of a learning process also enhancing results.

In this paper, 177 samples is selected from the PolyU3D palmprint database, and each of them provided five samples. Each 3D palmprint is transformed into a 2D vector, and the Four-Patch Local Binary Pattern (FPLBP) approach is employed. For improvement, a modified one called MFPLBP was proposed, and its parameters are tuned by employing a genetic algorithm imposing crossover constraints and mutation. A correlation distance measure is utilized for matching the results against the database template.

II. Proposed Work

We selected five samples from the PolyU3D palmprint database for every subject among the 177 subjects of this study. Our goal is to convert every 3D palmprint into a 2D vector using the Four-Patch Local Binary Pattern (FPLBP) approach. A new variant of FPLBP, called MFPLBP, is proposed to optimize the parameters of FPLBP with a genetic algorithm that has constraints in crossover and mutation. After processing, the outcomes are correlated with saved database templates on a correlation distance basis, as illustrated in Figure 1.

For clarity, the algorithm generates a random binary vector to illustrate the crossover operation. In this case, genes are selected from the first parent where the vector is 1, and from the second parent where the vector is 0. For example:

p1 = [a b c d e f g h]; p2 = [1 2 3 4 5 6 7 8] Random crossover vector = [1 1 0 0 1 0 0 0] The resulting child vector becomes: [a b 3 4 e 6 7 8]. The parameters used for this process are as follows: Population size: 6; Maximum chromosome length: 4 (bits per chromosome); Crossover rate: 0.8 (probability of crossover); Mutation rate: 0.1 (probability of mutation per bit). For the identification process, the number of imposters is 389,400, and the number of clients is 1,770.

A. Four-Patch Local Binary Pattern (FPLBP)

The Four-Patch Local Binary Pattern (FPLBP) is an advanced texture descriptor that builds on the traditional Local Binary Pattern (LBP) method, offering improved feature extraction for more distinct textures. This technique is particularly useful in areas like image recognition, classification, and texture analysis. Unlike the standard LBP, which focuses on individual pixel intensity values, FPLBP analyzes small patches of pixels, allowing for more detailed local texture representations. This makes FPLBP less sensitive to noise and lighting variations [17].

In FPLBP, the face is divided into patches, typically of size $k \times k$. The patch is represented by a center pixel or intensity value pooled over the patch, e.g., mean, median, or Gaussian-weighted sum. The center patch is compared with adjacent patches in a given pattern, e.g., grid or circular neighborhood. Binary value (0 or 1) is assigned to each neighboring patch based on whether its intensity is lower or higher than the center patch. Summation of these binary values provides a code to the local texture pattern. The code is typically decoded to a decimal value for ease, and one histogram of pattern is formed for describing the texture of the image [17].

FPLBP has a few advantages over LBP. Because it is operating on patches instead of pixels, FPLBP is less sensitive to noise caused by local changes in intensity. It is also less sensitive to overall changes in intensity because it is operating on summed-up patch values, so it is more invariant to lighting changes. Lastly, due to the use of patches, FPLBP is more proficient in detecting high-resolution texture details and thus performs well in application tasks such as texture classification [17].

This method has been used extensively in tasks like texture classification, face detection, image retrieval, and medical imaging. For example, it can isolate different textures from images, maintain accurate facial expressions, or show patterns in medical images such as X-rays or MRIs. Unlike the direct pixel intensity comparison of the original LBP operator, FPLBP's patch-based method gives a more descriptive texture description, leading to improved robustness and performance on a broad variety of applications. But at the expense of a slight increase in computational complexity [17].

B. Modified Four-Patch Local Binary Pattern (MFPLBP)

The Modified Four-Patch Local Binary Pattern (MFPLBP) has an optimization process that improves the efficiency of the texture descriptor. The process reduces redundancy and increases the strength of feature extraction by adjusting FPLBP parameters. The extra step improves the efficiency of the process and makes it capable of processing various datasets and applications [17].

The optimization phase, subject to crossover constraint, is utilized for adjusting FPLBP parameter values in order to best describe features. An objective function is defined for assessing the performance of the descriptor, e.g., recognition or classification accuracy. Optimization methods, often evolutionary algorithms like Genetic Algorithms (GA), are utilized for adjusting parameters such as patch size, number of neighboring patches, or aggregation methods (e.g., mean or weighted sum) [17].

Limitation of crossing is a process implemented in the course of optimization to restrict the occurrence of only positive parameter combinations. In genetic algorithms' crossover, parameters from different solutions are blended to create new ones. Crossing limitation is supposed to restrict consideration of only useful combinations to prevent overfitting and redundant complexity. This limitation is targeted at the optimization process to focus on enhancing performance solutions that are generalizable. After finding the optimal parameters, they are utilized to initialize the FPLBP descriptor. The FPLBP technique is then utilized by splitting the image into patches, taking the summation of the intensity values for each patch, and comparing the center patch with the neighboring patches with the assistance of the optimized parameters. These comparisons are then converted into binary patterns, which are then converted into decimal numbers and graphed into a histogram in order to preserve the texture of the image [17].

The FPLBP is optimized, and its optimization is enhanced by the crossover constraint. The optimized FPLBP has several benefits, including the fact that the optimization process customizes the FPLBP to the desired dataset or application, thus a more precise and versatile FPLBP. The crossover constraint also prevents irrelevant or unnecessarily complex patterns from being generated, thus a more efficient and resilient descriptor. Thirdly, by combining optimization and FPLBP, the texture description is made more precise, improving performance under adverse conditions, i.e., noisy images or non-uniform illumination conditions [17].

Finally, the Modified FPLBP with crossover constraint pre-adjusts the parameters of the descriptor in a way that the texture features to be extracted are not only efficient but also highly discriminative. It is therefore appropriate for high-level computer vision tasks. The crossover and mutation optimized parameters are expressed by the equation [17].

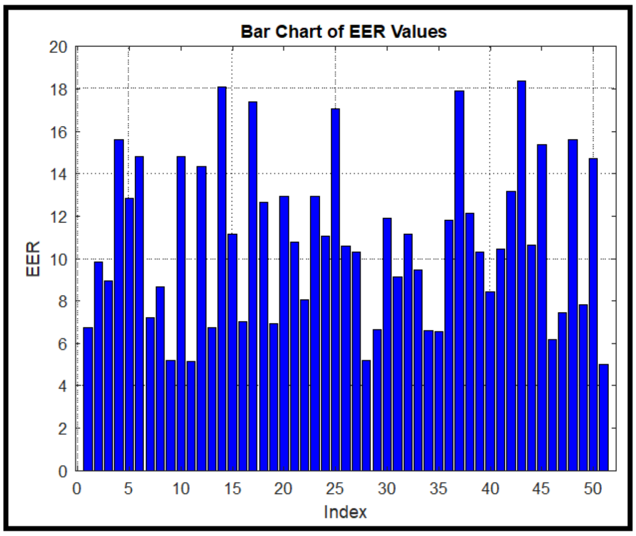

Fig. 2. The relationship between the parameters and the EER

$$FPLBP_{r_1,r_2,S,\omega,\alpha}(P) = \sum_{i}^{S/2} f(d(C_i, C_{2,i+\alpha} modS))- d(C_{1,i+\frac{S}{2}}, C_{2,i+\frac{S}{2}+\alpha} modS))2^i \quad (1)$$

C. Dataset Descriptions

For this study, we utilized the contact-free 3D/2D hand images database (Version 1.0) from the Hong Kong Polytechnic University. This dataset is available online at 3D Hand Database. The 3D hand images included in the database were captured using the commercially available Minolta VIVID 910 3D scanner over the course of four months. The participants, aged between 18 and 50, came from diverse ethnic backgrounds and were mostly institute staff and students. The time between two data collection sessions ranged from one week to three months. There were no restrictions on ambient lighting during indoor photo sessions. Users were asked to hold their right hand in front of the scanner at a distance of 0.7 meters, without any restrictions or hand jewelry. The images had a resolution of 640 and were numbered sequentially.

D. Results and discussion

In this study, 177 participants are selected, and five samples are taken from each individual in the PolyU3D palmprint database. Each 3D palmprint is processed and converted into a 2D vector, followed by the application of the Four-Patch Local Binary Pattern (FPLBP) method. A modified version of FPLBP, called MFPLBP, is introduced, which optimizes the FPLBP parameters using a genetic algorithm with crossover constraints and mutation. The correlation distance metric is then used to compare the results with the values in the database template. Table I presents 10 selected results from a total

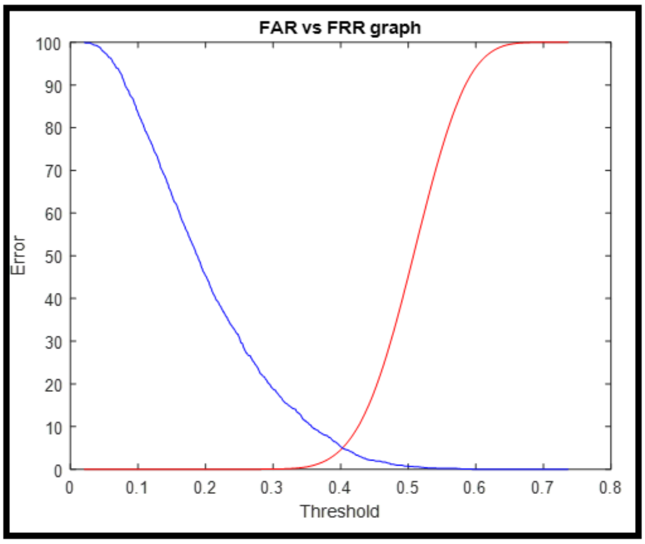

Fig. 3. FAR vs FRR curve

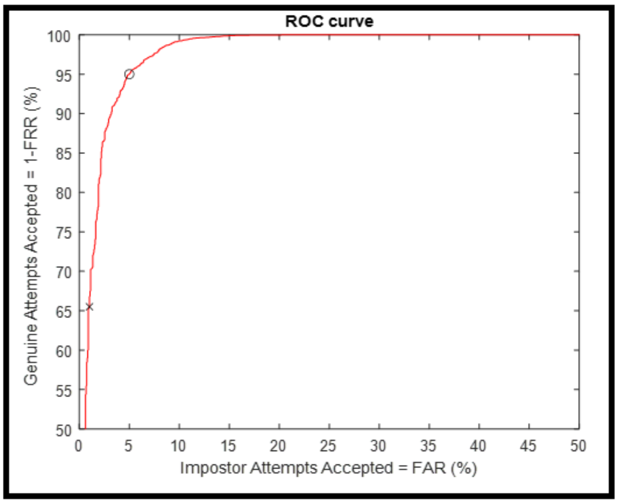

Fig. 4. ROC curve

of 50 results, as shown in Figure 2. Figure 2 illustrates the relationship between the parameters (represented by the index in the figure) and the EER. The proposed method achieves the lowest EER at 4.988%. The results are then compared with other state-of-the-art methods [18], [19], [20], [15], [17].

TABLE I
SELECTED RESULTS BETWEEN THE OPTIMIZED PARAMETERS AND EER FOR THE MFPLBP

Parameters	EER %
r1=4; r2=2; S=4; W=5, alpha =6; tau=0.05	6.723
r1=2; r2=4; S=6; w=5; alpha=1; tau=0.07	5.197
r1=4; r2=7; S=4; w=5; alpha=5; tau=0.01	6.726
r1=1; r2=5; S=4; w=2; alpha=2; tau=0.05	6.906
r1=3; r2=7; S=6; w=5; alpha=6; tau=0.07	5.199
r1=3; r2=4; S=10; w=5; alpha=8; tau=0.07	6.661
r1=7; r2=10; S=12; w=4; alpha=3; tau=0.02	6.595
r1=6; r2=3; S=10; w=8; alpha=4; tau-=0.13	6.549
r1=6; r2=1; S=8; w=10; alpha=3; tau=0.12	6.165
r1=8; r2=5; S=10; w=7; alpha=9; tau=0.04	4.988

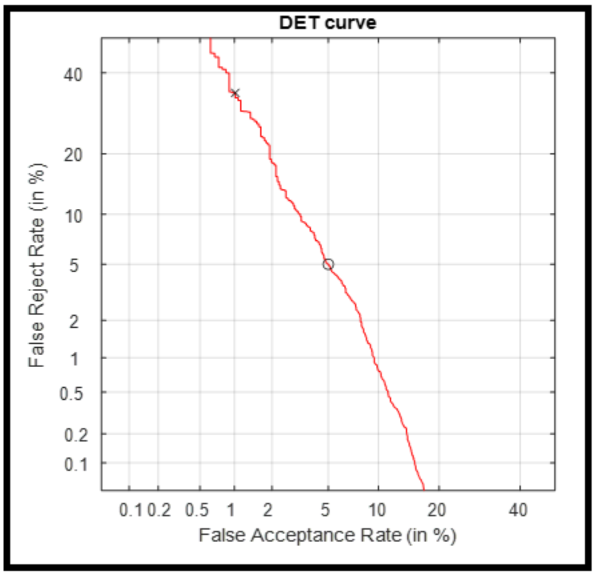

Fig. 5. DET curve

Figure 3 shows the False Accept Rate (FAR) and False Reject Rate (FRR) of the palmprint pattern identification method. This helps in selecting the optimal threshold for specific applications by showing the trade-off between the two rates Figure 4 shows a Receiver Operating Characteristic (ROC) curve to evaluate the effectiveness of the palmprint pattern recognition method. The curve displays a trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at different threshold values. By comparing biometric identification methods using the ROC curve and AUC, the best operating point can be determined.

Figure 5 shows a detection error trade-off (DET) curve, which illustrates the relationship between the false accept rate (FAR) and the false reject rate (FRR). It helps assess the performance of biometric systems when the cost of incorrect rejection is higher than the cost of false acceptance. A successful system is represented by a DET curve in the bottom left corner, indicating low error rates for both false rejections and false acceptances. Table II compares various feature extraction techniques for palmprint-based identification. These include Enhanced Local Line Binary Pattern (ELLBP), Local Line Binary Patterns (LLBP), Local Binary Patterns for FOK (LBP-FOK), Local Directional Number (LDN), Three Patch Line Binary Patterns (TPLBP), and Modified Four Patch Line Binary Patterns (MFPLBP). As shown in Table II, the proposed MFPLBP performs better, achieving the lowest EER of 4.988.

TABLE II
COMPARISONS THE PROPOSED WORK WITH OTHER STATE OF THE ART WORK

Reference	Method	Parameters	EER
[18]	ELLBP	N=17, w1=0.7 and w2=0.3	13.782
[19]	LBP FOK	N =5	25.099
[20]	LLBP	N=17	14.065
[15]	LDN	Mask Gaussian and Σ =0.85	16.999
[17]	TPLBP	r=2; S=8; w=3; alpha =5; tau=0.01	11.751
Proposed MFPLBP	FPLBP with Genetic algorithm phases	r1=8; r2=5; S=10; w=7; alpha=9; tau=0.04	4.988

III. Conclusions

Palmprint recognition's unique characteristics and stability made it a reliable biometric method for personal identification. This study presented the Modified Four-Patch Local Binary Pattern (MFPLBP), an innovative approach for recognizing three-dimensional (3D) palmprints. The proposed method enhanced the traditional Four-Patch Local Binary Pattern (FPLBP) by incorporating improved texture descriptor extraction and adaptive weighting techniques, tailored to the complex surface features of 3D palmprints. The MFPLBP proved resistant to noise and lighting changes while effectively capturing fine local variations. A thorough experimental evaluation using a publicly available 3D palmprint dataset showed that MFPLBP outperformed other advanced methods and traditional LBP-based techniques in terms of recognition accuracy and computational efficiency. The results highlighted MFPLBP's potential as a reliable and efficient tool for 3D palmprint-based biometric identification in real-world applications.

Acknowledgment

The authors would like to thank the department of Electrical Engineering at Mustansiriyah University, College of Engineering, Baghdad, Iraq as well as the Technical Engineering College of Mosul at the North Technical University in Mosul, Iraq, for their constant support, encouragement.

References

[1] L. Zhang, Y. Shen, H. Li, and J. Lu, "3d palmprint identification using block-wise features and collaborative representation," *IEEE transactions on pattern analysis and machine intelligence*, vol. 37, no. 8, pp. 1730–1736, 2014. [Online]. Available: https://doi.org/10.1109/TPAMI.2014.2372764

[2] X. Bai, N. Gao, Z. Zhang, and D. Zhang, "3d palmprint identification combining blocked st and pca," *Pattern Recognition Letters*, vol. 100, pp. 89–95, 2017. [Online]. Available: https://doi.org/10.1016/j.patrec.2017.10.008

[3] L. Fei, B. Zhang, Y. Xu, W. Jia, J. Wen, and J. Wu, "Precision direction and compact surface type representation for 3d palmprint identification," *Pattern Recognition*, vol. 87, pp. 237–247, 2019. [Online]. Available: https://doi.org/10.1016/j.patcog.2018.10.018

[4] D. Samai, K. Bensid, A. Meraoumia, A. Taleb-Ahmed, and M. Bedda, "2d and 3d palmprint recognition using deep learning method," in *2018 3rd international conference on pattern analysis and intelligent systems (PAIS)*. IEEE, 2018, pp. 1–6. [Online]. Available: https://doi.org/10.1109/PAIS.2018.8598522

[5] D. Zhang, V. Kanhangad, N. Luo, and A. Kumar, "Robust palmprint verification using 2d and 3d features," *Pattern Recognition*, vol. 43, no. 1, pp. 358–368, 2010. [Online]. Available: https://doi.org/10.1016/j.patcog.2009.04.026

[6] D. Zhang, G. Lu, W. Li, L. Zhang, and N. Luo, "Palmprint recognition using 3-d information," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 39, no. 5, pp. 505–519, 2009. [Online]. Available: https://doi.org/10.1109/TSMCC.2009.2020790

[7] D. Zhang, W.-K. Kong, J. You, and M. Wong, "Online palmprint identification," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 25, no. 9, pp. 1041–1050, 2003. [Online]. Available: https://doi.org/10.1109/TPAMI.2003.1227981

[8] A. Meraoumia, S. Chitroub, and A. Bouridane, "2d and 3d palmprint information and hidden markov model for improved identification performance," in *2011 11th International Conference on Intelligent Systems Design and Applications*. IEEE, 2011, pp. 648–653. [Online]. Available: https://doi.org/10.1109/ISDA.2011.6121729

[9] A. R. Rivera, J. R. Castillo, and O. O. Chae, "Local directional number pattern for face analysis: Face and expression recognition," *IEEE transactions on image processing*, vol. 22, no. 5, pp. 1740–1752, 2012. [Online]. Available: https://doi.org/10.1109/TIP.2012.2235848

[10] S. Manjunatha, A. Guruprasad, and P. Vineesh, "Face analysis by local directional number pattern," *Int. J. Eng. Res. Gen. Sci*, vol. 3, no. 1, pp. 1400–1410, 2015.

[11] B. Vishnudharan and K. Anusudha, "A discriminative model for facial expression recognition using local directional number pattern," in *2016 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)*. IEEE, 2016, pp. 349–352. [Online]. Available: https://doi.org/10.1109/ICCICCT.2016.7987972

[12] R. R. Rose, A. Suruliandi, and K. Meena, "Local texture description framework-based modified local directional number pattern: a new descriptor for face recognition," *International Journal of Biometrics*, vol. 7, no. 2, pp. 147–169, 2015. [Online]. Available: https://doi.org/10.1504/IJBM.2015.070928PDF

[13] A. Srikrishna, C. S. H. Priya, and P. A. Kiran, "Face recognition with varying facial expression using local directional number pattern," in *2015 IEEE Power, Communication and Information Technology Conference (PCITC)*. IEEE, 2015, pp. 615–619. [Online]. Available: https://doi.org/10.1109/PCITC.2015.7438071

[14] G. G. S. Kumari, "A person and proclamation identification by using local directional number pattern."

[15] R. R. O. Al-Nima, H. Maher, and N. T. Saeed, "Patterns identification of finger outer knuckles by utilizing local directional number," *International journal of electrical and computer engineering systems*, vol. 14, no. 9, pp. 1059–1068, 2023. [Online]. Available: https://doi.org/10.32985/ijeces.14.9.10

[16] S. Arivazhagan, R. A. Priyadharshini, and S. Sowmiya, "Face recognition based on local directional number pattern and anfis classifier," in *2014 IEEE International conference on advanced communications, control and computing technologies*. IEEE, 2014, pp. 1627–1631. [Online]. Available: https://doi.org/10.1109/ICACCCT.2014.7019384

[17] L. Wolf, T. Hassner, and Y. Taigman, "Descriptor based methods in the wild," in *Workshop on faces in'real-life'images: Detection, alignment, and recognition*, 2008.

[18] R. R. O. Al-Nima, "Signal processing and machine learning techniques for human verification based on finger textures," Ph.D. dissertation, Newcastle University, 2017. [Online]. Available: http://hdl.handle.net/10443/3982

[19] R. R. O. Al-Nima, M. K. Jarjes, A. W. Kasim, and S. S. M. Sheet, "Human identification using local binary patterns for finger outer knuckle," in *2020 IEEE 8th Conference on Systems, Process and Control (ICSPC)*. IEEE, 2020, pp. 7–12. [Online]. Available: https://doi.org/10.1109/ICSPC50992.2020.9305779

[20] A. Petpon and S. Srisuk, "Face recognition with local line binary pattern," in *2009 Fifth International Conference on Image and Graphics*. IEEE, 2009, pp. 533–539. [Online]. Available: https://doi.org/10.1109/ICIG.2009.123