International Journal of Advanced Science and Research
www.allsciencejournal.com
ISSN: 2455-4227
Received: 23-06-2026, Accepted: 23-07-2026, Published: 07-08-2026
Volume 11, Issue 3, 2026, Page No. 32-35

Improved three-patch local binary pattern by Artificial Rabbits Optimization for 3D Palmprints identification

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Abstract
Palmprints have received significant recognition and gain attention. However, Three-Dimensional palmprints can provide more explorations, especially in the case of identification. In this paper, we propose Improved Three-Patch Local Binary Pattern approach as a feature extraction. It exploits the state-of-the-art method of Artificial Rabbits Optimization. The Artificial Rabbits Optimization produces and helps in investigating the parameters of Three-Patch Local Binary Pattern. Therefore, it allows obtaining the improved approach with high performance. The database of Hong Kong Polytechnic University Contact-free 3D/2D (PolyU3D2D) has been employed in this study. The results show interesting and promising outcomes. The final accuracy of 92.37% is successfully achieved.

Keywords: 3D Palmprints, Artificial Rabbits Optimization, three-patch local binary pattern, identification

Introduction
The Palm is part of the hand. It is helpful in daily life activities. It has significant features that can effectively be used for recognition [1]. In this case it is called palmprint. There are more than many types of recognition as verification and identification [2]. The essential difference between these two types is in their matching ideas. Verification matching idea considers one-to-one scenario, where biometric features are compared to only on record of enrolled data. Whilst, identification matching idea utilizes one-to-all scenario, where biometric features are compared to all enrolled data records [3]. Identification is concentrated in this work.

Much more features may be obtained if Three-Dimensional (3D) is utilized for palmprint. In the literature, some studies were carried out for 3D palmprints in the case of recognition. In 2015, Ni *et al.* introduced a study of 3D palmprint in which new recognition algorithm was presented. Dempster-shafer fusion theory was utilized [4]. In 2016, Zheng *et al.* suggested 3D feature descriptor. It was a new descriptor. It was recovered from a Two-Dimensional (2D) image of palmprint [5]. In 2017, Yang *et al.* illustrated recognizing 3D palmprint. Representation of shape index was used. Fragile bits was utilized [6]. In 2018, Samai *et al.* investigated 2D and 3D palmprints in the case of identification. Efficient identification system was presented. Deep learning method was used [7]. In 2019, Chaa *et al.* explored unsupervised deep learning for 3D palmprints. Convolutional deep learning model was utilized. Support Vector Machine (SVM) was exploited [8]. In 2020, Bai *et al.* worked for identification with 3D palmprint. Blocked histogram was employed. Improved sparse representation was applied [9]. In 2021, Korichi *et al.* suggested personal identification system. Effective 3D and 2D palmprint identification was investigated. RelifF and transfer learning deep were exploited [10]. In 2023, Micucci and Iula analyzed 3D ultrasound recognition performance. Multimodal biometric system was illustrated. It merged between palmprint and hand-geometry [11]. In 2025, Al-Kaltakchi *et al.* proposed a new feature extraction descriptor. It was called Modified Four-Patch Local Binary Pattern (MFPLBP). It was employed for identifying 3D palmprints [12].

This study aims to consider 3D palmprints identification. An approach named Improved Three-Patch Local Binary Pattern (ITPLBP) is proposed. It is an improved version of Three-Patch Local Binary Pattern (TPLBP) [13]. It exploits the modern optimization method of Artificial Rabbits Optimization (ARO) [14].

The sections of this paper are distributed as follows: 1st section is for the introduction, 2nd section is for the proposed method, 3rd section is for the results and discussions and 4th section is for the conclusion.

Proposed Approach
As mentioned, ITPLBP approach is proposed here. It improves the previous version of TPLBP [13]. As such, TPLBP will be firstly illustrated. It is a descriptor which can be used for the feature extraction. It deals with blocks of values. Figure 1 shows the essential demonstration of this method.

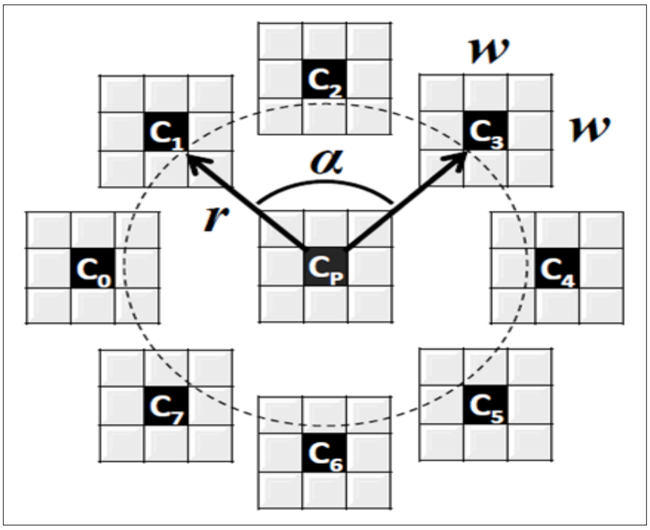

Fig 1: Essential demonstration of TPLBP as given in [13]

TPLBP can be expressed by the following equation:

$$TPLBP_{r,S,w,\alpha} = \sum_i^S f(d(C_i, C_p) - d(C_{i+\alpha \bmod S}, C_p))2^i \quad \ldots(1)$$

where: $TPLBP_{r,S,w,\alpha}$ represents the outcome of TPLBP, r represents the radius of a ring of patches, S represents the distributed uniformly patches of the ring, w represents the width and height of a patch, α represents pairs of ring patches, C_i and $C_{i+\alpha \bmod S}$ represent two surrounded patches around the central patch C_p, $d(.,.)$ represents a distance function, and f is denoted as:

$$f(x) = \{1\ if\ x \geq \theta\ 0\ if\ x < \theta \quad \ldots(2)$$

Where: θ represents a small tolerance [13].

Hence, the parameters r, S, w, α and θ are difficult to be predicted for the applied task, ITPLBP approach is proposed to address this issue. As mentioned, it utilizes a modern optimization which has the ability to predict best values for certain parameters. Given that ARO is a state-of-the-art optimization method, it has been exploited here. ITPLBP equation can be provided as follows:

$$ITPLBP_{r^*,S^*,w^*,\alpha^*} = \sum_i^S f(d(C_i, C_p) - d(C_{i+\alpha \bmod S}, C_p))2^i \quad \ldots(3)$$

where: $ITPLBP_{r,S,w,\alpha}$ represents the outcome of ITPLBP, r^* represents the optimized value of r, S^* represents the optimized value of S, w^* represents the optimized value of w and α^* represents the optimized value of α. Similarly, θ^* represents the optimized value of θ in the modified equation of f which can be defined as:

$$f(x) = \{1\ if\ x \geq \theta^*\ 0\ if\ x < \theta^* \quad \ldots(4)$$

ARO has the capability to predict the values of determined parameters. It simulates the nature survival algorithm of rabbits. Rabbits mainly eat leafy weeds, forbs and grass, they are herbivores. They look for foods which are far from their nests, they do not feed near grass from their holes. This prevents the holes from being specified by predators. Such strategy is considered as the exploration [14].

It has been investigated that there is another survival strategy for rabbits, which is related to random hiding. They dig multiple burrows around their nests, in order to escape the hunters or predators. They have strong legs that allow them to run fast. Furthermore, they can stop immediately while running, run back or turn sharply to escape chasing with a zigzag motion. So, this can effectively raise their survival probability. Such strategy is considered as the exploitation [14].

By well balancing between the exploration and exploitation, ARO can be efficiently employed for solving many optimization problems.

Results and Discussions

First of all, the employed database is called Hong Kong Polytechnic University Contact-free 3D/2D (PolyU3D2D). This database consists of patterned 3D scans for palm-side or inner surface of hands. The 3D hand images have been captured by using a 3D digitizer of type (Minolta VIVID 910). The data were acquired for span of over 4 months. 177 participants have been participated in this database. They were mainly staff and students. The age of participants is ranged from 18 to 50 years old. They were from various ethnic backgrounds. No restrictions were conditioned the hand position. Participants were instructed to take off any wearing jewelry. Nevertheless, black background was used. Participants were just asked to hold their hands and palms approximately parallel to the scanner's image plane in the imaging area. Live visual feedback was provided for participants. The resolution of each 3D or 2D image equals to 640 × 480 pixels. This database composes of many 2D and 3D hand images. It can be exploited in advanced researches for the fields of 3D palmprint recognition, 2D palmprint recognition and hand geometry [15].

In this study, 3D palmprints of the 177 participants have been employed. Number of identification comparisons for participants equals to 1770. Whereas, number of identification comparisons for imposters reaches to 389400. The comparisons are based on computing correlation distance. Moreover, the employed 3D palmprints have been reshaped to 2D vectors to facilitate their using.

The values of ITPLBP parameters have been produced by exploiting ARO. They are benchmarked here as: $r^* = 2$, $S^* = 4$, $w^* = 4$, $\alpha^* = 6$ and $\theta^* = 0.2$. These are obtained after setting ARO to: the number of rabbits = 5, number of variables = 5, number of iterations = 20, and the range of each variable is [1,10] except the last variable, where its range is [0,0.1].

A high accuracy of 92.37% is attained, where Equal Error Rate (EER) of 7.63 is obtained. Figures 2, 3 and 4 show performances for the 3D palmprints identification by using the proposed ITPLBP approach. They provide the curves of False Acceptance Rate (FAR), False Rejection Rate (FRR), Receiver Operating Characteristic (ROC) and Detection Error Tradeoff (DET).

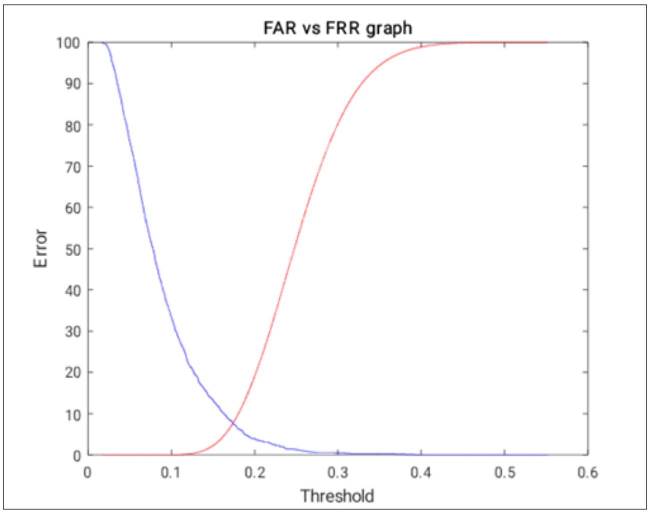

Fig 2: FAR and FRR curves for the 3D palmprints identification by using the proposed ITPLBP approach

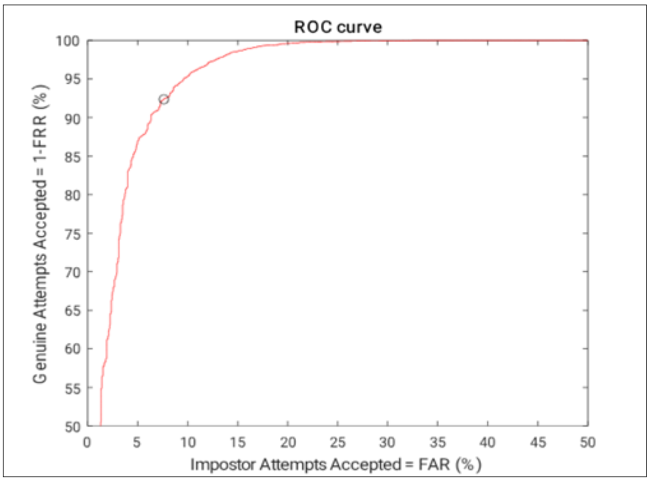

Fig 3: ROC curve for the 3D palmprints identification by using the proposed ITPLBP approach

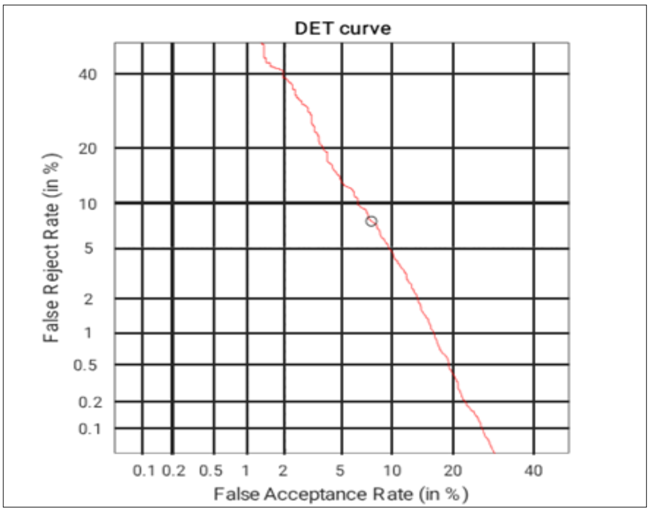

Fig 4: DET curve for the 3D palmprints identification by using the proposed ITPLBP approach

By the demonstrations of these figures, it can be yield that consistency, success and performances are achieved. For the purpose of comparison, our proposed ITPLBP approach is evaluated with other methods namely: Local Directional Number (LDN) [16], Assigned Local Directional Number (ALDN) [20], Local Line Binary Pattern (LLBP) [19], Enhanced Local Line Binary Pattern (ELLBP) [17], Assigned Local Binary Patterns (ALBP) [18] and TPLBP [13]. Table 1 shows accuracies comparison between various methods.

Table 1: Accuracies comparison between various methods

Reference	Method	Parameters	Accuracy (%)
[18]	ALBP	$N = 5$	74.90
[20]	ALDN	Mask of type Gaussian and $= 0.85$	83.00
[19]	LLBP	$N = 17$	85.93
[16]	LDN	kirsch (mask size = 3)	86.10
[17]	ELLBP	$N = 17$, $w_1 = 0.7$ and $w_2 = 0.3$	86.22
[13]	TPLBP	$r = 2$, $S = 8$, $w = 3$, $\alpha = 5$ and $\theta = 0.01$	88.25
Proposed Approach	ITPLBP	$r^* = 2$, $S^* = 4$, $w^* = 4$, $\alpha^* = 6$ and $\theta^* = 0.2$	92.37

From this table, it can be investigated that the lowest performance is recorded for ALBP [18], where it has attained the accuracy of 74.90%. Other accuracies of range from 83.00% to 88.25% are reported for other compared methods. Obviously, our proposed approach of ITPLBP outperforms and surpasses other compared methods, involving state-of-the-art, as it benchmarks the accuracy of 92.37%.

Conclusion

To conclude, this paper has presented the proposed ITPLBP approach. It is an improved version of TPLBP. It has exploited the state-of-the-art algorithm of ARO, where it has helped in producing the values of certain parameters (r^*, S^*, w^*, α^* and θ^*).

The outcomes can be highlighted as a promising path forward for further research. As such, the proposed ITPLBP approach has obtained the high accuracy of 92.37%, where it has attained the low EER of 7.63. Performances comparison with other methods have also been provided, these are LDN, ALDN, LLBP, ELLBP, ALBP and TPLBP. It appears that ITPLBP has achieved superiority over all compared methods.

Acknowledgment

We thank:

- The Hong Kong Polytechnic University Contact-free 3D/2D Hand Images Database version 1.0.
- The Northern Technical University, Ministry of Higher Education and Scientific Research (MOHESR), Iraq.

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