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Finger Texture Biometric Verification Exploiting Multi-scale Sobel Angles Local Binary Pattern Features and Score-based Fusion

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Abstract

In this paper a new feature extraction method called Multi-scale Sobel Angles Local Binary Pattern (MSALBP) is proposed for application in personal verification using biometric Finger Texture (FT) patterns. This method combines Sobel direction angles with the Multi-Scale Local Binary Pattern (MSLBP).

The resulting characteristics are formed into non-overlapping blocks and statistical calculations are implemented to form a texture vector as an input to an Artificial Neural Network (ANN). A Probabilistic Neural Network (PNN) is applied as a multi-classifier to perform the verification. In addition, an innovative method for FT fusion based on individual finger contributions is suggested. This method is considered as a multi-object verification, where a finger fusion method named the Finger Contribution Fusion Neural Network (FCFNN) is employed for the five fingers. Two databases have been employed in this paper: PolyU3D2D and Spectral 460nm (S460) from CASIA Multi-Spectral (CASIA-MS) images. The MSALBP feature extraction method has been examined and compared with different Local Binary Pattern (LBP) types; in classification it yields the lowest Equal Error Rate (EER) of 0.68% and 2% for PolyU3D2D and

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CASIA-MS (S460) databases, respectively. Moreover, the experimental results revealed that our proposed finger fusion method achieved superior performance for the PolyU3D2D database with an EER of 0.23% and consistent performance for the CASIA-MS (S460) database with an EER of 2%.

Keywords: Finger texture, finger fusion, local binary pattern, biometric verification, probabilistic neural network

1. Introduction

Biometric patterns have been explored for many years in different applications such as security systems. Many biometric traits have been explored such as irisprint [1, 2], sclera [3, 4], face [5, 6], fingerprint [7, 8] and palmprint [9, 10],

- ⁵ however, there are still opportunities for performance improvement. Hand images contain rich features, which could be utilized in terms of biometric identification, verification or classification. Examples of these are hand geometry [11] and finger geometry [12]. Despite the geometrical features being easy to acquire, they still result in low recognition performance and they are usu-
- ¹⁰ ally fused with other biometrics to enhance performance. Rich patterns can be found inside the skin of the hand such as the hand veins [13], finger veins [14] and palm veins [15]. Yet, the essential obstacle of these patterns is that they require an infrared camera with a special environment to capture such images. Fingerprints [16] have been studied for many years and can be considered as
- ¹⁵ one of the first effective biometrics suitable for personal recognition. However, it has been reported that recognition performance from fingerprints could be affected by ageing [17, 18] and diabetes [19]. The palm print [20] has also been investigated as it consists of reliable and stable patterns. The major concern with the palm print is that if the palm is subject to injury this may lead to
- ²⁰ incorrect recognition.

On the other hand, the biometric Finger Texture (FT) has attracted significant attention as in [21, 22]. The FT pattern is distributed among the five fingers. So, the five fingers of the hand can contribute together to give precise recognition or verification decision. If an accident happens to any finger, there will

still be four fingers that can be gathered to give good verification performance. Therefore, a multi-object biometric system based on the five FT fingers can be created. The FTs can offer a robust recognition performance as they have various human-specific features such as wrinkles, apparent lines, dermal patterns and ridges. The main parts of FTs for a single finger are demonstrated in Fig.

30 1.

The FTs include patterns which are clearly visible, so, a low cost camera can be used to capture such images. Also, these characteristics are reliable, even unique between identical twins, formed from birth and generally stable throughout the individual's life [23]. In addition, there are some further advantages such as

acceptability, as they are not affected by emotional feelings or even tiredness, they have rich characteristics, can be captured by a low resolution device and are easy to access [24].

The two main contributions in this paper are:

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• A new descriptor called the Multi-scale Sobel Angles Local Binary Pattern (MSALBP). This operator has been created by utilizing the Sobel vertical and horizontal edge angles of the FTs. Then, a Multi-Scale Local Binary Pattern (MSLBP) has been applied to the Sobel edge angles image. After that these images have been blocked and Coefficient of Variance (CV) calculations are exploited to describe the feature vector. Extensive



Figure 1: The main parts of FTs for a single finger

• A novel multi-object fusion method named Finger Contribution Fusion Neural Network (FCFNN) for the FTs of the five fingers (index, middle, ring, little and thumb). This fusion is inspired from the contribution of each finger according to its region size. For instance, the contribution score of the thumb finger in the personal verification is not equal to the contribution score of the index or middle finger, in the same case.

The overall aims of this paper are to enhance the personal verification performance by implementing and verifying the suggested MSALBP and FCFNN approaches. Various comparisons are performed to demonstrate the ability and efficiency of the proposed methods.

The rest of this paper is organised as follows: in Section II the related work will be illustrated. The main procedure of the verification process will be described in Section III. In Section IV the theoretical part of the Local Binary Pattern (LBP), improved LBP types and proposed MSALBP will be given. Section V will explain the fundamentals of the Probabilistic Neural Network (PNN) and

the suggested FCFNN fusion method. The results, discussions and comparisons will be illustrated in Section VI. Finally, the conclusion of this paper will be given in Section VII.

2. Literature review

- The idea of using FTs as a biometric identifier first appeared about 10 years ago, when it was investigated in [21] as a part of a multi-biometric identification system combined with the palm. Eigenvector techniques were used to produce eigenfinger and eigenpalm images. Also, in this work the contribution rate of each finger was calculated. After that, a combination of palm, FTs, and hand
- ⁷⁰ geometry was used to produce a low cost multi-biometric recognition system in [25]. Furthermore, different types of fusion were evaluated: decision fusion, score-level fusion and feature fusion. It was recorded that decision fusion obtained the most satisfactory results. The FTs of the main four fingers (index,

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middle, ring and little) with their fingerprints were studied in [22] as parts of

- ⁷⁵ a comparison work. However, the main drawback was that only small parts of the FTs were applied in the system as explained in our prior work [26]. A biometric verification system was presented in [23], where an automatic tracking algorithm was implemented to acquire the hand images from a device with a real-time video camera. In this work the FTs were combined with the palm
- print to achieve a robust verification. Different feature extraction approaches were used for each part of the hand, in particular the ridgelet transform was used for the FTs and the wavelet Gabor transform was used for the palm print. Similarly, the same multi-modal biometric system was described in [27]. Next, a fusion of a palm print, hand geometry and finger surfaces from 2D and 3D hand
- images was implemented in [28] to enhance the contactless hand verification. A low verification performance was recorded with the Equal Error Rate (EER) = 6% for the PolyU3D2D database. On the other hand, vein and texture finger images were evaluated in the case of identification in [14]. The major problem of this work was that the database was acquired for a small region of the fingers. In
- addition, just two fingers were employed (the index and/or the middle finger). This could be the reason why the authors used two types of fusion, holistic and non-linear fusions, both of which are mainly based on the vein characteristics. From the previous literature, it can be seen that the FTs have been used as a part of a multi-modal biometric, where it could be studied intensively and fully
 employed to improve the recognition results.
- In terms of the feature extraction, the improved LBP neighbours structure was proposed in [29] to analyze the inner knuckle print. This scheme consists of the following steps: Gabor filtering, mean filtering and LBP image using the improved LBP operator. Then, uniform LBP values have been established for
- each pixel, and binary images have been produced for each LBP uniform value. Limited features have however been utilized in this publication, just parts of the inner knuckles were applied. Similarly, a novel approach to also use part of the inner knuckles was adopted in [30], basically, the middle knuckles of the middle and ring fingers. The database was acquired from touchless fingers restricted by

¹⁰⁵ a peg and a back-plate. The derived line detection with the Gabor filter were used as feature extractions. It is clear from the above listed work that just parts of FTs have been used.

In our prior work [26] FTs were intensively studied, and ROIs were fully extracted for the four fingers (index, middle, ring and little) and a new feature

- extraction method was adopted named "image feature enhancement". The best results in that work yielded EER = 4.07% for the PolyU3D2D database. Moreover, in [31] the following contributions have been presented: (1) a robust finger segmentation method to collect the five finger images from a hand image; (2) An enhanced feature extraction method is proposed called Enhanced Local Line
- Binary Pattern (ELLBP); and (3) Verification performance is evaluated for limited views or even missing fingers. Furthermore, a novel approach was described to enhance the verification rates in the case of missing a part or full FT by salvaging features embedded in the trained PNN. The EER values have been benchmarked to 0.34% for the PolyU3D2D database and 3% for the CASIA-MS
- (S460) database. In this paper we intend to decrease further the EER and increase the verification performance by applying a new LBP operator and using a novel FCFNN fusion method. In addition, the proposed feature extraction operator has significantly obtained a better timing performance of 0.002 seconds compared to various LBP operators as is shown later in Table 4.
- It is worth mentioning that there are several recent publications, such as [32, 33, 34, 35, 36], which have employed the Finger-Knuckle-Print (FKP) database [37] to develop a new biometric identifier based on the outer finger knuckles. There are however several difficulties associated with this suggested database. First of all, the finger outer knuckles are unique and reliable patterns, but they
- do not have a normal protection like the inner FTs. Secondly, the acquiring device which has been designed to collect this database has a single peg with a specific angle to restrict the finger in the suitable bending degree. Therefore, if any dislocation in the knuckle position happened, it could lead to a wrong verification decision as explained in [36]. Thirdly, the database has been col-
- 135 lected to include only middle outer knuckles for just two fingers (middle and

index fingers), so, it includes only limited features and overlooked the other outer knuckles which may be important in increasing the recognition performance. On the other hand, biometric systems have been designed in [38, 39] to capture the outer finger knuckles by using cameras located at the top of these devices, but these designed systems require a particular environment with fixed

specification measurements and their database was not provided online.

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3. Proposed methodology

In this work, the Hong Kong Polytechnic University Hand Images Database V1 is employed. This database contains a large number of two dimensional hand images [40]. Thus, the fingers can be extracted as proposed in our previous work [31], where full ROIs have been considered for the main four fingers (index, middle, ring and little). In addition to the thumb fingers, which have been extracted later, full ROIs have been used with the other fingers in this paper. After that, the features are extracted from each finger using our proposed descriptor. Firstly, a Sobel filter is applied in both directions horizontally and vertically on the extracted fingers. The resulting images will be fused or combined together by calculating the directional angle between the horizontal and vertical images. An MSLBP is then applied on the directional angle ma-

each block. After that, all the CV values of fingers will be concatenated to produce one single vector for each sample. The resulting vectors are separated into training and testing groups. The training vectors are firstly used to train a PNN. Then, the testing vectors will be applied to test the results. The stages of the proposed algorithm are given in Fig. 2. The proposed feature extraction
method will be evaluated to benchmark the best parameters. In addition, the

trix. Next, the resulting image will be blocked. The CV can be calculated for

¹⁶⁰ method will be evaluated to benchmark the best parameters. In addition, the proposed method will be compared against the related literature. An innovative FCFNN fusion method has also been suggested to improve the verification performance. The key idea of this method is to use the fingers' contribution scores in the verification decision because each finger has a dif-



Figure 2: The block diagram of the suggested scheme for the feature extraction and the fusion of the five fingers

- ¹⁶⁵ ferent contribution score to prove the personal verification. For example, the contribution score of the thumb is not similar to the contribution score of the middle finger due to the fact that the area of the thumb is smaller than the area of the middle finger. Thus, we propose that each finger will be trained by a separate PNN. Hence, one neural network is implemented during the testing
- phase by establishing an additional hidden layer called a contribution layer. In this layer, each finger will generate its contribution scores. Then, a summation fusion is calculated to combine these contribution scores together. Finally, the decision will be undertaken to generate outputs. Significant improvement in terms of EER has been noticed after using the FCFNN. Also, there is an ad-
- ditional advantage of this network, which is the flexible structure. So, if any finger is amputated it can be easily deleted by removing its connections and the last verification decision will depend on the remaining fingers.

4. Local Binary Pattern (LBP) feature extraction

4.1. Standard Local Binary Pattern (LBP)

The LBP was firstly introduced in [41] as a method of texture analysis. An example of the LBP code is shown in Fig. 3. Basically, the image is first divided into 3×3 sub-blocks. In each sub-block a comparison is carried out between the value of the center pixel and the values of its surrounding 8 neighbour pixels as depicted in Fig. 3. The results of this comparison is a logical number; if the center value is smaller than the neighbour pixel value then assign '0' to this location and if the center value is greater than or equal to the neighbour pixel value put '1' in this location. After that, a weighted sum equation is applied to convert the binary number to the decimal code. The following equation can be considered to calculate the LBP code:

$$LBP = \sum_{P=0}^{7} s(g_p - g_c)2^p , \ s(x) = \begin{cases} 1 & , & x \ge 0 \\ 0 & , & x < 0 \end{cases}$$
(1)

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where: g_c is a center pixel of the 3×3 sub-block, g_p is the circular surrounding neighbour pixels and s is the LBP transformation.



Figure 3: An example of computing the LBP code for a 3×3 window

The resulting LBP image is usually divided into non-overlapped blocks. The histogram is applied on each part and the histogram bins are concatenated to ¹⁹⁵ produce a single vector, which is considered as a feature vector of the original image. However, some recent papers suggested to use the resultant image of the LBP directly instead of generating the histograms such as [29, 42, 43]. This is because utilizing the histograms may result in losing important spatial information as reported in [29]. Therefore, in our work we have used the LBP image codes as a basis for the texture patterns.

4.2. Multi-Scale Local Binary Pattern (MSLBP)

To enhance the LBP feature Ojala *et al.* in [44], proposed an MSLBP operator $LBP_{P,R}$ using a circular neighbourhood of the pixels having different spatial sampling P and different radius R. The LBP values for the re-sampled pixels which are not located on the original grid are calculated by using the bilinear interpolation [44]. Fig. 4 shows different MSLBP operators.

Hence, the original LBP equation (1) has been modified to the following MSLBP



Figure 4: Different MSLBP operators, from the left $LBP_{8,1}$, $LBP_{16,2}$ and $LBP_{24,3}$

equation:

$$MSLBP_{P,R} = \sum_{P=0}^{P-1} s(g_p - g_c)2^p , \ s(x) = \begin{cases} 1 & , & x \ge 0 \\ 0 & , & x < 0 \end{cases}$$
(2)

where g_p is the gray level of sampled value and g_c is the center value.

4.3. Proposed Multi-scale Sobel Angles Local Binary Pattern (MSALBP)

Our proposed feature descriptor which is called MSALBP is designed to produce an effective feature extraction for the FTs. It starts by filtering the finger images with the Sobel operator masks, where each operator mask is related to a direction (vertical or horizontal). Both direction operators are shown in Fig. 5a and Fig. 5b, respectively [45]. It is true that this is not the first time the Sobel method is used with the LBP as in [46, 20, 47]. However, the structure is different, where in [46, 20] the Sobel edge images were used with different operator directions and then each of their vectors were concatenated together to construct the feature vector. This resulted in very large vectors, where in

- [46] the feature vector size was equal to 2124 values and in [20] the feature vector size consisted of 4248 values. In [47] a descriptor called the Gradient Directional Pattern (GDP) has been generated. In this descriptor the Sobel angle orientations had been considered, but it utilized a comparison tolerance
- function with the center pixel in the LBP operator with the histogram feature extraction. The essential problem in this work is that the comparison based on the tolerance function caused texture loss from the image. In particular if the comparison value is more or less than the center pixel \pm of the tolerance, this

value would be set to zero.



Figure 5: The Sobel operator masks:

(a) The Sobel vertical operator.

(b) The Sobel horizontal operator.

The sign directions of the Sobel operators are empirically determined to obtain consistent performance and make fair comparisons. To combine the horizontal and vertical features of an image, let Gx be the convolved image with the horizontal operator mask and Gy the filter convolved image with the vertical operator mask. So, both filtered images can be fused together by using one of the following equations [45]:

$$|G| = \sqrt{Gx^2 + Gy^2} \tag{3}$$

$$\theta = atan2(Gy, Gx) \tag{4}$$

where |G| represents the amplitude of the gradient, θ represents the angle direction of the edges and *atan*2 represents the four-quadrant inverse tangent described in [48] but used in Matlab for the range of $[-\pi, \pi]$.

It has been cited that the amplitude/magnitude equation is not robust to provide directional information as in a phase/angle calculation [49, 50], whereas

²⁴⁵ angle features can efficiently describe the gradients of certain patterns with less sensitivity to the pixel level values than the amplitude features. On the other hand, the amplitude equation can be influenced by noise, brightness and range value problem as highlighted in [51]. In this work, the angle direction matrix has been chosen to generate our new MSALBP operator. This is because it at-

tained better results than the amplitude as will be demonstrated in the results and discussion section.

Henceforth, the following equation can be used to implement the proposed MSALBP on the edge angles direction image.

$$MSALBP_{P,R} = \sum_{P=0}^{P-1} s(gt_p - gt_c)2^p , \ s(x) = \begin{cases} 1 & , & x \ge 0 \\ 0 & , & x < 0 \end{cases}$$
(5)

- where gt_p and gt_c represent the neighbour and the center pixels of each subblock after the Sobel angle direction image respectively. To obtain the best implementation for the FT patterns, different values of LBP radius and neighbour parameters have been examined.
- Hence, the MSALBP values are distributed in the pixels of the Region of Interest (ROI) of each finger before the blocking operation. That is to establish the feature vector, the resulting images have been divided into non-overlapping blocks. CV values have been calculated in each block according to equations (6), (7) and (8), respectively [52]:

$$M_{bl} = \frac{1}{n} \sum_{i=1}^{n} bl_i \tag{6}$$

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$$STD_{bl} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (bl_i - M_{bl})^2}$$
(7)

$$CV_{bl} = \frac{STD_{bl}}{M_{bl}} \tag{8}$$

where $n, bl, i, M_{bl}, STD_{bl}$ and CV_{bl} are respectively the number of pixels in each block, a block of 5×5 pixels, pixels' pointer in each block, the average value of the block pixels, the standard deviation value of the block pixels and the CV of the block pixels.

The resulting values have been concatenated into a one dimensional vector to be used later in the neural network stage. The reason for using the CV calculation to represent the feature vector is because of its facilities and characteristics such as: it is easy to implement, it well describe the variances of the features, depends on two measurements (the standard deviation and the mean), it is simple and it has effective computations.



Figure 6: Image analysis of the MSALBP operator: Each row represents a finger; from the top: thumb, index, middle, ring and little respectively. While, the first column is assigned for original FT images, the second column shows the horizontal edge images, the third shows the vertical edge images and the last row represents the MSLBP of the angle images

Fig. 6 shows example of the five FT images with their horizontal edges, vertical edges and the MSLBP images of the angle images.

5. Artificial Neural Network (ANN)

An ANN is one of the most famous trained methods which can be used effectively for various applications such as classification and verification. There are two main types of ANN, supervised and unsupervised. Basically, the term supervised refers to the network that require targets during the training phase. Whilst, unsupervised networks do not require targets. In the training phase the neural network parameters will be learned for specific training patterns while in the testing phase the neural network will give decisions to the input vectors

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in the testing phase the neural network will give decisions to the input vectors which have not been seen before [53]. In this paper, a PNN is employed to verify people according to their FTs. Furthermore, an innovation fusion method has been applied during the testing phase to increase the verification rate and decrease the EER.

5.1. Probabilistic Neural Network (PNN)

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A PNN is considered as a multi-classifier ANN. It is also termed as a multiple layer neural network as it consists of an input layer, pattern layer, summation layer and decision layer. Principally, the PNN utilizes the following probability density function [53, 54]:

$$f_A(\mathbf{x}) = \frac{1}{(2\pi)^{l/2}\sigma^l} \frac{1}{m_A} \sum_{i=1}^{m_A} exp\left[-\frac{(\mathbf{x} - \mathbf{x}_{Ai})^T (\mathbf{x} - \mathbf{x}_{Ai})}{2\sigma^2}\right]$$
(9)

where \mathbf{x}_{Ai} represents the i^{th} input training pattern from the class A, l represents the dimension of the input vectors, m_A is the number of training patterns in class A, σ is a spread controlling parameter for the probability density function and it is here equal to 0.1, and $(.)^T$ is the transpose function. In this work we set m_A to be the same for each class, which we denote as p, and c is the number of classes.

The node outputs of the pattern layer are computed according to equation (10) [53, 55]:

$$Z_{i,j} = exp\left[-\frac{(\mathbf{x} - \mathbf{w}_{i,j})^T (\mathbf{x} - \mathbf{w}_{i,j})}{2\sigma^2}\right] ,$$

$$i = 1, 2, ..., p , \quad j = 1, 2, ..., c \quad (10)$$

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where $Z_{i,j}$ represents the output of a pattern node, **x** represents the input vector

 $\mathbf{x} = [x_1, x_2, ..., x_n]^T$ and $\mathbf{w}_{i,j}$ is the i^{th} known feature example in the class j as the complete weight vector can be represented by $\mathbf{w}_{i,j} = [w_1, w_2, ..., w_n]^T$.

The summation layer will calculate the probabilistic values from the pattern layer for the same input vector to each class by using the following equation:

$$S_j = \frac{1}{p} \sum_{i=1}^p Z_{i,j} \quad , \quad j = 1, 2, ..., c$$
 (11)

where S_j represents the summation layer values.

The decision layer will follow a competitive rule called (the winner takes all rule). This rule can be represented in the following equation (12):

$$D_j = \begin{cases} 1 & if \ S_j = max \\ 0 & otherwise \end{cases}, \quad j = 1, 2, ..., c$$
(12)



Figure 7: The general form of the FLFPNN for five FT fingers

where max represents the extracted maximum S_j value.

- Basically, during the training phase the PNN is aiming to create the weights $\mathbf{w}_{i,j}$, where these weights are important to establish a non-linear relationship between the inputs and the targets. The weights will be stored after completing the training. Then, these weights will be used in the testing phase to predict the outputs according to the input patterns. In the PNN the weight values are generated exactly equal to the input values.
- The general form of the PNN is illustrated in Fig. 7. In this figure the Feature Level Fusion with the PNN (FLFPNN) method based on concatenating the finger vectors is used in the input layer. This method was described and used in [56, 57].

5.2. Proposed finger fusion method

After analysing the standard PNN, it can be noticed that the information of the input layer will be shared in the output. Therefore, each finger will have the same contribution if the traditional PNN is used. The finger contribution scores are important due to the fact that each finger has a different contribution as reported in [21]. From this point it can be argued that the performance of the verification can be enhanced during the testing phase after including the contribution score of each finger. Fig. 8 illustrates the skeleton of the proposed fusion method. It consists of these multiple layers: input layer, pattern layer, contribution layer summation layer and decision layer. Hence, we propose to add an extra layer called the "contribution layer" so that different contributions can be acquired from each finger.

This method imposes that each finger should use a separate PNN during the training phase to benchmark its contribution scores within the established weights in the pattern layer. On the other hand, during the testing phase a score fusion can be implemented easily after the contribution layer, where each finger will determine its contribution score.

Next, the contribution score values for the fingers are fused together using the



Figure 8: The proposed FCFNN method including the contribution layer

sum rule fusion. After that, the score fusion of all fingered will be fed to the decision layer.

Therefore, equation (10) is modified as follows:

$$Z_{i,j}^{Fing} = exp\left[-\frac{(\mathbf{x}^{Fing} - \mathbf{w}_{i,j}^{Fing})^T (\mathbf{x}^{Fing} - \mathbf{w}_{i,j}^{Fing})}{2\sigma^2}\right],$$

$$i = 1, 2, ..., p \quad , \quad j = 1, 2, ..., c \quad (13)$$

The score values are fused together according to (14) and (15) as shown below:

$$CO_j^{Fing} = \frac{1}{p} \sum_{i=1}^p Z_{i,j}^{Fing} , \quad j = 1, 2, ..., c$$
 (14)

$$S_j = \sum_{Fing=1}^{5} CO_j^{Fing} , \quad j = 1, 2, ..., c$$
 (15)

where Fing represents the finger object and CO_j^{Fing} represents the contribution nodes in the contribution layer.

Nevertheless, equation (12) is still the same in our FCFNN, where the winner takes all rule is the basis of the output decision. Same as in PNN, during the training phase the FCFNN is aiming to build the $\mathbf{w}_{i,j}^{Fing}$ weights then storing

them at end of the training. These weights will be utilized in the same network during the testing phase to examine the input patterns by producing the predicted FCFNN outputs.

Flexibility is one of the main advantages of our proposed method. Thus, if any person has lost any finger it will be easy to remove its connections from the FCFNN. In addition, the FCFNN method has the same advantages as the PNN in modifying the number of users but the concatenation is not needed in the case of the FCFNN; moreover, a training stage is not needed to establish the matching weights between the inputs and their targets. Furthermore, it is not affected by the local minima in the error performance function as in the

³⁴⁵ networks trained with the backpropagation algorithm.

6. RESULTS AND DISCUSSIONS

The experiments are conducted using two databases: the Hong Kong Polytechnic University Contact-free 3D/2D (PolyU3D2D) Hand Images Database (Version 1.0) [40] and S460 spectral band from the CASIA Multi-Spectral (CASIA-MS) Palmprint image database (Version 1.0) [58]. The first database contains

8850 finger images which belong to 1770 hands acquired from 177 subjects. The hand imaging were collected by the Minolta VIVID 910 3D digitizer. The age range for the participant varies from 18 to 50 [40]. This database has been divided into two equal parts; one part is used in the training phase and the other in

- the testing phase following the works of [26, 28]. Therefore, 4425 finger images have been used in the training phase and rest of the finger images have been employed in the testing phase. This will ensure that the neural networks will test new finger images which have not given before. In the CASIA-MS database, multi-spectral light sensors have been used to capture different features for the
- hand images. Principally, the skin of an inner hand surface shows various characteristics if different light spectra are applied. This is due to the penetration of the given spectrum wavelength. A total of 100 users contributed with their right and left hand images. Six samples were captured in two sessions. Multispectral wavelengths, which were generated by the provided lighting, were used
- to capture six image patterns at one certain time. The utilized spectra had the wavelengths of 460nm, 630nm, 700nm, 850nm, 940nm and white illumination. In this study, S460 spectral band images from the CASIA-MS database are employed, because the spectrum wavelength 460nm contains the FTs as stated in [59, 60]. From each participant 5 hand images have been used in the training
- phase and the remaining hand images have been utilized in the testing phase following [26, 28, 31].

As we have two major contributions in this paper, this section is divided into two subsections. The first one concentrates on evaluating the proposed MSALBP feature extraction while the second one will discuss the suggested FCFNN finger fusion.

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6.1. Evaluating the Multi-scale Sobel Angles Local Binary Pattern (MSALBP) feature extraction

This subsection investigates different aspects in the proposed MSALBP with the traditional FLFPNN method. First of all, as the suggested MSALBP is employing the Sobel edge detector, different edge analysis techniques have been examined. Table 1 shows comparisons between the performance of applying the Roberts, Prewitt or Sobel techniques to the same FT system. The Equal Error Rates (EERs) are calculated by utilizing the two databases PolyU3D2D and CASIA-MS (S460) as shown in Table 1.

Database	Multi-scale Angles Local Binary Pattern	Parameters	EER
	based edge detection method		
	Roberts		3.50%
PolyU3D2D	Prewitt	P=8, R=1	1.02%
			~
	Sobel		0.79%
	Roberts		0.79% 16%
CASIA-MS	Sobel Roberts Prewitt	P=8, R=1	0.79% 16% 6%

Table 1: Comparisons between different scenarios of edge detection angles

In this table, the basic Local Binary Pattern (LBP) parameters (Neighbour pixels (P) = 8 and Radius (R) = 1) have been integrated in all edge detection methods. Among all these edge detectors, the Sobel operator attained the best results.

The Sobel operator achieved the best result because the mask weight is high compared to the Roberts and Prewitt operators. Having low mask values as is the case with the Roberts and Prewitt operators will not generally reveal the key features of the FT.

After the Sobel direction filters two output components can be computed: the amplitude and angle. We have selected the angle as it gives the best results in

terms of the EER as illustrated in Table 2, which clearly indicates that using the Sobel angle directions in the MSALBP gives better results than using the amplitude. This is because the amplitude is affected by the illumination, imaging contrast and camera gain while the angle directions is not. So, the angle patterns will have more effective information than the amplitude level patterns.

PolyU3D2D database				
Edge detection method	Combination operation	LBP parameters	EER	
Poherta	Amplitude	P=8, R=1	1.13%	
Roberts	Angle	P=8, R=1	3.50%	
Duomitt	Amplitude	P=8, R=1	1.24%	
Frewitt	Angle	P=8, R=1	1.02%	
Cabal	Amplitude	P=8, R=1	2.15%	
Sobel	Angle	P=8, R=1	0.79%	
C.	ASIA-MS (S460) datal	oase		
Edge detection method	Combination operation	LBP parameters	EER	
Dahanta	Amplitude	P=8, R=1	3%	
Koberts	Angle	P=8, R=1	16%	
	Amplitude	P=8, R=1	6%	
Prewitt	Angle	P=8, R=1	6%	
Sobel	Amplitude	P=8, R=1	8%	
	Angle	P=8, R=1	5%	

Table 2: Amplitude values versus angle directions for different edge detection methods

Table 2 shows that the Sobel method with the angle obtains better performance than the Sobel method with the amplitude. Therefore, the EER was reduced from 2.15% with the amplitude to 0.79% using the angle for the PolyU3D2D database and from 8% to 5% for the CASIA-MS (S460) database. In contrast,
the Roberts method with the amplitude yields better results than using the angle calculation. That is, the verification performance was enhanced from 3.50% with the angle computation to 1.13% with the amplitude operation for the PolyU3D2D database and from 16% to 3% with the amplitude operation for the CASIA-MS (S460) database. Furthermore, utilizing the Prewitt method with the amplitude has very similar performance as with the angle calculation. As illustration, the EER percentage is slightly decreased from 1.24% with the

EER percentage of 6% was achieved with either the amplitude or angle for the CASIA-MS (S460) database.

- The reason for these results is related to the vertical and horizontal operators before the computation of amplitude or angle. For the Roberts operation, only diagonal edges are considered and these edges are not consistent with the FT patterns. On the other hand for the Prewitt and Sobel operations, both vertical and horizontal edges are analysed. Nevertheless, Prewitt is more sensitive to low
- ⁴²⁰ contrast images than Sobel. This explains why it attained similar performance to the Soble operation for the PolyU3D2D database and no improvement is observed for the lower quality CASIA-MS (S460) database. Hence, the Sobel operation with the angle that uses the ratio of the outputs of the horizontal and vertical operators appears to be the best choice here as it almost achieves the

⁴²⁵ most acceptable performance.

Secondly, the MSALBP is tested under different blocks size: 3×3 , 5×5 , 7×7 , 9×9 , 11×11 , 13×13 and 15×15 . The best block size is found to be 5×5 as it has achieved the best results as shown in Fig. 9.



Figure 9: The performance of the MSALBP (P=8, R=1) by using various block sizes

It can be seen from Fig. 9 that the best blocking choice is 5×5 as it achieved

⁴³⁰ the lowest EER compared to other blocking. Moreover, varying the blocking size to more than or less than the suitable size will increase the verification error rate.

Following [61], the testing parameters are: (P = 8, R = 1), (P = 8, R = 2), (P = 16, R = 2), (P = 16, R = 3) and (P = 24, R = 3) respectively. Table 3

⁴³⁵ shows different EERs compared against different MSALBP parameters, as well as, different LBP types. In the case of establishing fair comparisons, similar normalization in the ROI size, block size, feature vector preparation and FLF-PNN method have been implemented to all LBP types.

It can be seen from Table 3 that using the MSALBP with a multi-scale of P

- 440 = 8 and R = 2 parameters yielded the best verification performance for the PolyU3D2D and CASIA-MS (S460) databases compared with the other parameters such as P = 16, R = 2 and P = 16, R = 3. The general rule here is that increasing the radius R to more than 2 will cause a loss of the micro textures; whereas, decreasing the radius to 1 will include the micro-textures and the em-
- ⁴⁴⁵ bedded noise as well. On the other hand, the number of surrounded pixels P is related to the amount of processed information and increasing this number will increase the redundant data. Also, our proposed MSALBP feature extraction attained the best results compared to other LBP types, which confirms the efficiency of our approach. The EERs for the Simplified LBP (SLBP) are 1.47% for
- the PolyU3D2D database and 31% for the CASIA-MS (S460) database. This is because the SLBP lacks the use of the directional weights which resulted in loss of important textures. The Three-Patch LBP (TPLBP) recorded the same EERs of 1.47% for the PolyU3D2D database and 31% for the CASIA-MS (S460) database with its default parameters: w = 3, r = 2, S = 8, $\alpha = 5$ and $\tau = 0.01$.
- The main problem here is that when the TPLBP operator is applied to the low resolution FT images, it losses important texture information. This is because the TPLBP uses patches of sub-blocks instead of the pixels to generate its code values. For the same reason the Four-Patch LBP (FPLBP) with its default parameters: w = 3, r1 = 4, r2 = 5, S = 8, $\alpha = 1$ and $\tau = 0.01$, attained high error
- $_{460}$ rates equal to 9.38% for the PolyU3D2D database and 45% for the CASIA-MS

PolyU3D2D database				
Reference	Method	Parameters	EER	
Qian and Veldhuis [62]	SLBP	P=8	1.47%	
Wolf et al. [63]	TPLBP	w=3, r=2, S=8, α =5	1.47%	
		and $\tau = 0.01$		
	FPLBP	w=3, r1=4, r2=5, S=8,	9.38%	
		$\alpha = 1$ and $\tau = 0.01$		
Ahmed [47]	GDP	$\tau = 4$	1.36%	
Liu et al. [29]	ILBPN	n/a	10.17%	
Tong <i>et al.</i> [64]	LGC	n/a	1.24%	
Suggested approach	MSALBP	P=8, R=1	0.79%	
	MSALBP	P=8, R=2	0.68%	
	MSALBP	P=16, R=2	0.79%	
	MSALBP	P=16, R=3	1.02%	
	MSALBP	P=24, R=3	1.58%	
CA	SIA-MS (S4	60) database		
Reference	Method	Parameters	EER	
Qian and Veldhuis [62]	SLBP	P=8	31%	
Wolf et al. [63]	TPLBP	w=3, r=2, S=8, α =5	31%	
		and $\tau = 0.01$		
	FPLBP	w=3, r1=4, r2=5, S=8,	45%	
		$\alpha{=}1$ and $\tau{=}0.01$		
Ahmed [47]	GDP	$\tau = 4$	6%	
Liu <i>et al.</i> [29]	ILBPN	n/a	58%	
Tong <i>et al.</i> [64]	LGC	n/a	22%	
Suggested approach	MSALBP	P=8, R=1	5%	
	MSALBP	P=8, R=2	2%	
	MSALBP	P=16, R=2	4%	
	MSALBP	P=16, R=3	4%	
	MSALBP	P=24, R=3	9%	

Table 3: Comparison between the results of different LBP types

(S460) database, and again increasing the radius between the neighbour pixels and the center pixel will increase the error rate value. It can be seen from Table 3 that the GDP has attained high EERs with 1.36% for the PolyU3D2D database and 6% for the CASIA-MS (S460) database by using $\tau = 4$ (This best

- τ value has been determined after many experiments). As mentioned earlier, important textures have been lost in this method due to the use of the tolerance function in the comparison. On the other hand, the Improved LBP Neighbours (ILBPN) feature has been basically designed for the inner knuckle patterns and this could be the reason of why it achieved the largest EERs of 10.17% for the
- ⁴⁷⁰ PolyU3D2D database and 58% for the CASIA-MS (S460) database. The Local Gradient Coding (LGC) type which considered as a new type of LBP attained a better performance compared to the aforementioned method with EER equal to 1.24% for the PolyU3D2D database. This value is almost double the EER achieved with the proposed MSALBP method. Whereas, in the CASIA-MS
- (S460) database the EER value was 22% and this is higher than the value of the MSALBP. This is due to the database features as it provides different pattern concentrations than the normal lighting database.

As a result, the best performance has been recorded when the proposed MASLBP is employed with R = 2 and P = 8, where the EER is benchmarked to 0.68%

- ⁴⁸⁰ and 2% for the PolyU3D2D and CASIA-MS (S460) respectively. The timing performance of our operator is compared with several other methods as shown in Table 4. It can be clearly seen the proposed MSALBP operator achieves the best computation time where all the aforementioned operators are tested under the same environment (3.2 GHz Intel Core i5 processor with 8 GB of RAM).
- It is evident from Table 4 that the timings vary between some LBP types and are comparable between the others. These values depend on the processing time of each function. The ELLBP has reported a slower time than all of the compared operators. In the case of the suggested approaches, the MSALBP has declared the best calculation time as it efficiently calculates the useful information tak-
- ⁴⁹⁰ ing into account the suitable micro-textures to be analysed and the basic LBP process to be followed.

Reference	Method	Parameters	Time (sec.)
Qian and Veldhuis [62]	SLBP	P=8	0.03
Wolf <i>et al.</i> [63]	TPLBP	w=3, r=2, S=8, α =5	0.007
		and $\tau = 0.01$	
	FPLBP	w=3, r1=4, r2=5, S=8,	0.007
		$\alpha{=}1$ and $\tau{=}0.01$	
Ahmed [47]	GDP	$\tau = 4$	0.05
Liu et al. [29]	ILBPN	n/a	0.034
Tong et al. [64]	LGC	n/a	0.05
Al-Nima et al. [31]	ELLBP	N=17	0.06
Suggested approach	MSALBP	P=8, R=2	0.002

Table 4: The timing comparison between the different LBP operators for a single finger

6.2. Evaluating the Finger Contribution Fusion Neural Network (FCFNN) finger fusion

The suggested FCFNN method is evaluated and compared with the normal feature concatenated finger fusion method. Table 5 shows the differences between the two fusion methods in terms of the EER.

PolyU3D2D database				
Feature extraction Finger fusion		EER		
	FLFPNN	0.68%		
MSALBP (P=8, R=2)	FCFNN	0.23%		
CASIA-MS (S460) database				
Feature extraction	Finger fusion	EER		
	FLFPNN	2%		
MSALDP $(P=8, R=2)$	FCFNN	2%		

Table 5: The results of the two finger fusion methods

According to Table 5 a considerable improvement is achieved in the EER of the PolyU3D2D database. This 66% improvement is due to the key idea of using

the contribution score for each finger in the fusion process, where the stan-

dard FLFPNN method does not consider this issue. On the other hand, in the CASIA-MS (S460) database the same performance has been achieved for both fusion methods. This confirms the ability of the FCFNN to maintain the best results which could be obtained by the FLFPNN. Basically, the main problem with the CASIA-MS (S460) database is that its images have been collected un-

- der the wavelength spectrum of 460nm. It has been cited that various spectra provide different featured FT images. Usually, the strength of the vertical FT patterns are found to be less than the horizontal patterns for this database, whereas, they are usually higher when acquired under normal lighting [31]. This explains the difference.
- ⁵¹⁰ The summation fusion rule is used with the FCFNN method because it achieved the best performance in terms of EER compared to other rules such as the multiplication, maximization and minimization fusion rules as shown in Table 6.

PolyU3D2D database			
Feature extraction	Score fusion rule of the FCFNN	EER	
	Summation operation rule	0.23%	
MSALBP	Multiplication operation rule	0.45%	
(P=8, R=2)	Maximum operation rule	1.24%	
	Minimum operation rule 6.4		
CAS	IA-MS (S460) database		
Feature extraction	Score fusion rule of the FCFNN	EER	
	Summation operation rule	2%	
MSALBP	Multiplication operation rule	2%	
(P=8, R=2)	Maximum operation rule	6%	
	Minimum operation rule	15%	

Table 6: The EER of different fusion rules within the FCFNN

The multiplication rule attained an EER value of 0.45% for the PolyU3D2D database and this is approximately double the EER value of the summation

- rule. This is because that the multiplication causes variation change in the 515 score values after the operation. Whereas, the summation operation increases the score values according to the level of contribution. On the other hand, the maximum rule obtained a dissatisfying EERs with 1.24% for the PolyU3D2D database and 6% for and CASIA-MS (S460) database as its operation is based
- on selecting the maximum value among a group of values and this would neglect 520 the useful values that could enhance the results. As expected, the Minimum rule achieved a poor performance with an EER equal to 6.44% for the PolyU3D2D database and 15% for the CASIA-MS (S460) database because it collects the minimum values among a set of finger contribution score values and these values 525
- are basically referring to low contribution scores. The effect of losing or amputating one or more fingers on the recognition performance is investigated as shown in Table 7. The advantages of the FCFNN can be seen by the ability of this method to handle the missing fingers. On the other hand, in the FLFPNN it is not feasible to remove connections between the input layer and the pattern layer.
- Table 7 indicates the flexibility of the proposed FCFNN method, where any finger connections can be simply removed from the FCFNN structure. The reason for choosing the neighbouring fingers, such as ring+little and middle+ring+little, is that the neighbouring fingers are more likely to be amputated in reality than

- separate fingers. Table 7 also shows that increasing the number of removed fin-535 gers generally reduces the verification performance. Furthermore, it can be seen from this table that the EER values vary according to the finger contribution score, where each finger has different features according to the resolution and characteristics of its image.
- The testing time of this proposed neural network has been recorded. All the 540 experiment were conducted on a 3.2 GHz Intel Core i5 processor with 8 GB of RAM. The testing time was equal to about 0.0097 seconds per sample compared with 0.003 seconds per sample for the normal PNN. It can be seen that there is no serious drawback when using the proposed fusion method as the difference of
- the testing time is just a few milliseconds. Similarly, the training time of both 545

PolyU3D2D database			
Fingers fusion	Missing finger(s)	EER	
Index+Middle+Ring+Little	Thumb	0.34%	
Middle+Ring+Little+Thumb	Index	0.68%	
Index+Ring+Little+Thumb	Middle	0.68%	
Index+Middle+Little+Thumb	Ring	0.45%	
Index+Middle+Ring+Thumb	Little	0.34%	
Middle+Ring+Little	Thumb+index	1.24%	
Thumb+Ring+Little	Index+Middle	1.58%	
Thumb+Index+Little	Middle+Ring	0.57%	
Thumb+Index+Middle	Ring+Little	0.90%	
Ring+Little	Thumb+Index+Middle	2.71%	
Thumb+Little	Index+Middle+Ring	2.71%	
Thumb+Index	Middle+Ring+Little	1.58%	
CASIA-MS (S460) database			
CASIA-MIS (5460) database		
Fingers fusion	Missing finger(s)	EER	
Fingers fusion Index+Middle+Ring+Little	Missing finger(s) Thumb	EER 2%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb	Missing finger(s) Thumb Index	EER 2% 5%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb	Missing finger(s) Thumb Index Middle	EER 2% 5% 5%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb	Missing finger(s) Thumb Index Middle Ring	EER 2% 5% 5% 3%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Ring+Thumb	Missing finger(s) Thumb Index Middle Ring Little	EER 2% 5% 5% 3% 6%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Ring+Thumb Index+Middle+Ring+Thumb Middle+Ring+Little	Missing finger(s) Thumb Index Middle Ring Little Thumb+index	EER 2% 5% 5% 3% 6% 8%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Middle+Ring+Little Thumb+Ring+Little	S460) database Missing finger(s) Thumb Index Middle Ring Little Thumb+index Index+Middle	EER 2% 5% 5% 3% 6% 8% 11%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Little Middle+Ring+Little Thumb+Ring+Little Thumb+Index+Little	Missing finger(s) Thumb Index Middle Ring Little Thumb+index Index+Middle Middle+Ring	EER 2% 5% 5% 3% 6% 11% 6%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Ring+Thumb Middle+Ring+Little Thumb+Ring+Little Thumb+Index+Little Thumb+Index+Middle	Missing finger(s) Thumb Index Middle Ring Little Thumb+index Index+Middle Middle+Ring Ring+Little	EER 2% 5% 3% 6% 8% 11% 6% 7%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Ring+Thumb Middle+Ring+Little Thumb+Ring+Little Thumb+Hndex+Little Thumb+Index+Middle Ring+Little	Missing finger(s) Thumb Index Middle Ring Little Thumb+index Index+Middle Middle+Ring Ring+Little Thumb+Index+Middle	EER 2% 5% 5% 3% 6% 8% 11% 6% 7% 15%	
Fingers fusion Index+Middle+Ring+Little Middle+Ring+Little+Thumb Index+Ring+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Little+Thumb Index+Middle+Little Middle+Ring+Little Thumb+Ring+Little Thumb+Ring+Little Thumb+Index+Little Thumb+Index+Middle Ring+Little Thumb+Little	Missing finger(s) Thumb Index Middle Ring Little Thumb+index Index+Middle Middle+Ring Ring+Little Thumb+Index+Middle Index+Middle+Ring	EER 2% 5% 3% 6% 8% 11% 6% 7% 15% 19%	

Table 7: Removing a finger or fingers from the architecture of the FCFNN using the MSALBP feature extraction

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networks, the normal network given in Fig. 7 and our proposed separate five PNNs for each finger, has been recorded too. It was equal to 0.000038 seconds per sample for the normal PNN compared with 0.00018 seconds per sample for our suggestion. It is true that the five PNNs will take longer training time

compared to the traditional PNN, but this time difference is very small and negligible considering the significant improvement in the EER. In addition, the training time of the PNN is faster than the training time of a backpropagation neural network [65].

6.3. Comparison with prior work

Different comparisons with related works have been carried out. Besides the companions shown in Table 3, here we perform additional evaluations. Kanhangad *et al.* [28] have employed a CompCode method, as a feature extraction, with the Hamming Distance (HD), as a matching metric between the testing vectors and the templates, to the same database. In this work part of FTs for

- four main fingers (index, middle, ring and little) have been used. Our prior work in Al-Nima *et al.* [26] has explained that increasing the FT features would lead to decrease in the EER. So, the result of applying full FT features is better than the results of using limited FT features. From this point, in this paper all the five fingers have been applied for verification evaluation. Furthermore,
- their EERs have been compared with the results of the main four fingers. See Table 8. All of the aforementioned works adopted the same database (the Hong Kong Polytechnic University Hand Images Database V1). After analysing Table 8 it can be concluded that increasing the FT features improves the recognition performance. For example, including the full FT features of the four fingers
- reduced the EER from 5.42% to 4.07% in [26]. Also, involving the FT of the thumb generally decreases the EER further as it can be observed in [31]. Moreover, the best results can be achieved by using the MSALBP feature extraction with the FCFNN fusion method. The suggested approaches have recorded better EER value, which is 0.23%, than all of the reported prior EER values for the
- $_{\rm 575}$ PolyU3D2D database. Similarly, the proposed FCFNN has also been applied

Approach	database	Method	EER (four	EER (four	EER (five
			fingers and	FT fingers)	FT fingers)
			part of FTs)		
Kanhangad	PolyU3D2D	CompCode	6%	_	—
et al., 2011 [28]		+ HD			
Al-Nima	PolyU3D2D	IFE +	5.42%	4.07%	_
et al., 2015 [26]		FLFPNN			
Al-Nima	PolyU3D2D	LBP +	1.81%	_	_
et al., 2016 [66]		FLFPNN			
	PolyU3D2D	ELLBP +		0.45%	0.34%
		FLFPNN			
Al-Nima	IIT Delhi	ELLBP +		3.38%	1.35%
et al., 2016 [31]		FLFPNN			
	CASIA-MS	ELLBP +		5%	3%
	(S460)	FLFPNN			
	PolyU3D2D	MSALBP		0.79%	0.68%
		+ FLFPNN			
	PolyU3D2D	MSALBP		0.45%	0.23%
Proposed		+ FCFNN			
approachs	CASIA-MS	MSALBP		5%	2%
	(S460)	+ FLFPNN			
	CASIA-MS	MSALBP	_	2%	2%
	(S460)	+ FCFNN			

Table 8: Comparisons of EER performance with prior works

to the CASIA-MS S460 database and this method is still achieving the best performance of EER = 2% compared to 3% in our previous work [31], which confirms the robustness of this method.

To produce a comprehensive study, the Receiver Operating Characteristic (ROC) ⁵⁸⁰ curves have been generated by following the novel approach in [66]. The main processes of generating the ROC curve are: collecting the effective PNN output values from the summation layer; remapping these values according to the PNN classifications; computing the False Acceptance Rate (FAR) and the True Positive Rate (TPR), which mathematically equals to (1-False Rejection Rate

⁵⁸⁵ (FRR)), based on comparing the remapped values with the targets; producing



Figure 10: The ROC curves for the MSALBP(P=8,R=2) feature extraction with the FLF-PNN and FCFNN for the PolyU3D2D database (the axis ranges are reduced to make the figure clearer)



Figure 11: The ROC curves for the MSALBP (P=8,R=2) feature extraction with the FLF-PNN and FCFNN for the CASIA-MS (S460) database (the axis ranges are reduced to make the figure clearer)

a relationship between the FAR and the TPR for each class; generating one FAR and TPR for all classes by calculating the averages of FARs and TPRs respectively; and finally depicting the ROC curve [66]. Similarly, in this paper generating the ROC graphs has been extended to include the FCFNN method

as the effective score values of the FCFNN can be found in its summation layer (as for the PNN). Therefore, a similar strategy of establishing the ROC curve for the PNN can be followed in the FCFNN. See Figs. 10 and 11. It can be noted from the ROC graphs that the FCFNN method in general achieves the best results compared with the FLFPNN for the PolyU3D2D

database and attains similar EER performance for the CASIA-MS (S460) database. Secondly, it is confirmed that the MSALBP has the ability to analyse the vertical and horizontal textures which are the common patterns in the FTs. Other LBPs have shown different performance as each type has attained a specific result according to its characteristics as recorded in Table 3.

600 7. Conclusion

same conditions.

Two essential contributions were proposed in this paper, the first major contribution was introducing a new feature extraction method. This method consisted of the following: integrating the MSLBP with the angle directions from the Sobel filter to generate a robust feature descriptor called the MSALBP. The images from [40] were employed for this purpose. After extracting fingers from the hand images, the resulting fingers were divided into 5×5 blocks and the MSALBP was applied. Then the CV values were calculated to generate the feature variances vector. Then, a multi-classifier PNN was used effectively to verify people. A large number of finger images (4425) were employed in the training phase and a similar number was used in the testing phase. Furthermore, feature extraction stages were examined and compared with other LBP types under the

The second contribution introduced a novel fusion method. The key idea of this fusion is to use the contribution score of each finger before the personal verification decision, where each finger has a different contribution score according to its covered region size. Therefore, a multi-object biometric approach was proposed by utilizing the FTs of the five fingers. An innovation score fusion was described by creating a new hidden layer, named the contribution layer, in the FCFNN. A remarkable result was recorded after using this suggested fusion

⁶²⁰ method, where the verification error rate has been reduced from 0.68% to 0.23%. Additional advantage can be attained from the FCFNN which is the simplicity of removing any finger contribution score from its structure. The experimental results showed that there were significant improvement in the recognition performance compared to previous works.

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