

Palm print verification based deep learning

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ABSTRACT

In this paper, we consider a palm print characteristic which has taken wide attentions in recent studies. We focused on palm print verification problem by designing a deep network called a palm convolutional neural network (PCNN). This network is adapted to deal with two-dimensional palm print images. It is carefully designed and implemented for palm print data. Palm prints from the Hong Kong Polytechnic University Contact-free (PolyUC) 3D/2D hand images dataset are applied and evaluated. The results have reached the accuracy of 97.67%, this performance is superior and it shows that our proposed method is efficient.

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1. INTRODUCTION

Biometric recognition technology is considered by many fields such as finger texture (FT) verification [1, 2], speaker identification [3, 4], face texture recognition [5], iris print surveillance [6-8] and palm print recognition [9]. Palm print characteristic can be considered as one of interesting physiological biometrics as it involves rich features. It locates in the inner surface of a hand between the wrist and fingers. This surface covers different textures namely principal lines, wrinkles and ridges [10, 11], see Figure 1. These textures can easily be identified. Palm prints are formed between the third and fifth months of pregnancy and its superficial lines are appeared after the birth [12]. A palm print image can be acquired by using an inexpensive low resolution scanner or camera. As mentioned, the palm print comprises of three types of textures (principal lines, wrinkles and ridges). Each one of these textures can provide a unique structure. The appearance of overall palm print structures offers a significant basis for verifying individuals.

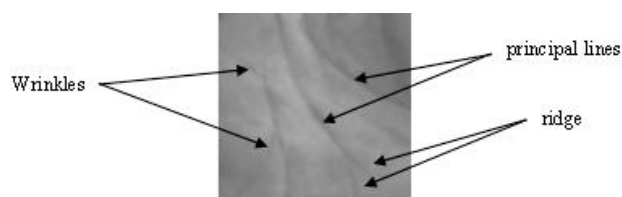


Figure 1. A palm print image and its textures of principal lines, wrinkles and ridges

In the literature, palm prints were exploited by a number of studies. In 2003, Xiangqian *et al.* illustrated a new palm print recognition method named the fisherpalm. In this method each pixel in the palm print image is considered in a high-dimensional space [13]. Tunkpien *et al.*, [14] presented a palm print identification study depending on the principal lines. It consisted of two main processes. Firstly, it considered the feature extraction by using consecutive filters to obtain the principal lines of a palm print. Secondly, it employed a K-Nearest Neighbor method to identify humans [14]. Amit Taneja [15] focused on personal verification by exploiting the neural network algorithm of backpropagation. Palm print features were collected here from color photographs, they were acquired after requesting participants to locate their hands on a special designed platform [15]. Raut *et al.*, [16] illustrated a personal identification method by extracting palm print lines. Morphological operation and statistical properties were utilized [16]. Bala and Nidhia [17] explored comparative palm recognition system by utilizing the maximum curvature and repeated method. Line tracking was considered to find out the repeated and broken lines [17]. Selvy *et al.*, [18] proposed palm print authentication system by applying the gray level co-occurrence matrix (GLCM). Then, the support vector machine (SVM) was used for classifying the obtained features [18]. In 2019, Gong *et al.* suggested an intelligent palm print recognition based on a convolutional neural network called Alexnet. Geometric shapes of palm prints were exploited [19]. In 2020, Poonia *et al.* approached a non-invertible template which can store the geometric data of palm print minutiae features. This study was concentrated on providing a robust palmprint template [20].

The aim and contribution of this work is suggesting a deep learning model for two-dimensional palm prints based verification. It is named the palm convolutional neural network (PCNN) network. The remaining sections are organized as follows: the theoretical basis of PCNN is illustrated in section 2, results and discussions are given in section 3 and the conclusion is clarified in section 4.

2. RESEARCH METHOD

In this section, the theoretical description of the PCNN will be provided. The basis of this network is the convolutional neural network (CNN). However, it is adapted and carefully designed for palm print images. It can accept and deal with palm print images in the case of verification. The idea of verification here is considering multiple output classes to confirm specific individuals as in [21].

The PCNN composes of multiple layers. These layers are the input, convolution, rectified linear unit (ReLU), pooling, fully connected (FC), softmax and classification layers. Firstly, the input layer is adapted to accept a single grayscale of segmented palm print image at a time. The size of each input is equal to 128×128 pixels. Secondly, the convolution layer is applied. This layer can analyze the features of the grayscale palm print image. The calculations of this layer can be expressed by (1) [22],

$$Z_{u,v,c}^l = B_c^l + \sum_{i=-k_h^l}^{k_h^l} \sum_{j=-k_w^l}^{k_w^l} \sum_{c^{l-1}=1}^{c^{l-1}} W_{i+k_h^l, j+k_w^l, c^{l-1}}^{c^l} z_{u+i, v+j, c^{l-1}} \quad (1)$$

where: $Z_{u,v,c}^l$ is an output of the convolution layer, (u,v) is a pixel coordinate, B_c^l is a channel bias, $W_{i,j,c^{l-1}}^{c^l}$ is the kernel weights, k_w^l and k_h^l are respectively the width and height of the convolution layer kernel, C is the channel number, l is the current layer, and $l-1$ is the previously layer.

Thirdly, the ReLU layer is employed. The function of ReLU layer is rectifying the negative values to zeros and passing the positive values of the previous layer. The (2) represents the ReLU function [23],

$$O_{u,v,c}^l = \max(0, Z_{u,v,c}^l) \quad (2)$$

where: $O_{u,v,c}^l$ is an output of the ReLU layer and max is the maximum operation.

Fourthly, the pooling layer is implemented. This layer can reduce the size of data by employing windowing and maximum operations. The maximum pooling calculations can be demonstrated by (3) [24],

$$q_{a,b,c}^l = \text{MAX}_{0 \leq a < p_h^l, 0 \leq b < p_w^l} O_{a \times p_h^l + a, b \times p_w^l + b, c}^l \quad (3)$$

where: $q_{a,b,c}^l$ is an output of the pooling layer, $0 \leq a^l < p_h^l$, p_h^l is the height of the pooled channel, $0 \leq b^l < p_w^l$, p_w^l is the width the pooled channel, $0 \leq c < c^l = c^{l-1}$, p_h is the height of each pooled window and p_w is the width of each pooled window.

Fifthly, a FC layer is utilized. This layer adapts between the number of nodes in the previous layer and number of required classes. The (4) represents the computation of FC layer [25],

$$g_r = \sum_{a=1}^{m_1^{l-1}} \sum_{b=1}^{m_2^{l-1}} \sum_{c=1}^{m_3^{l-1}} W_{a,b,c,r}^l Q(c)_{a,b}, \quad \forall 1 \leq r \leq m^l \quad (4)$$

where: g_r is an output of the FC layer, m_1^{l-1} is the width of previous channel, m_2^{l-1} is the height of previous channel, m_3^{l-1} is the number of previous channels, $Q(c)_{a,b}$ is the vector of pooling layer outputs, $W_{a,b,c,r}^l$ is the weights between the pooling and FC layers, and m^l is the required number of classes.

Sixthly, the softmax layer is used. This layer can provide probability distribution calculations for a current input with all classes. Softmax calculation can be given by (5) [25],

$$y_r = \frac{\exp(g_r)}{\sum_{s=1}^{m^{l-1}} \exp(g_s)} \quad (5)$$

where: y_r is an output of the softmax layer.

Finally, the classification layer is adapted to accept the number of subjects. This is the last PCNN layer, it exploits a competitive computation rule named the winner-takes-all. Figure 2 depicts the architecture of the proposed PCNN. In summary, the PCNN is an artificial model that can be counted with other artificial intelligence (AI) models as in [26-33]. It can be exploited for important security issues such as [34-41]. Appropriate parameters of PCNN have been evaluated as will be illustrated in the next section.

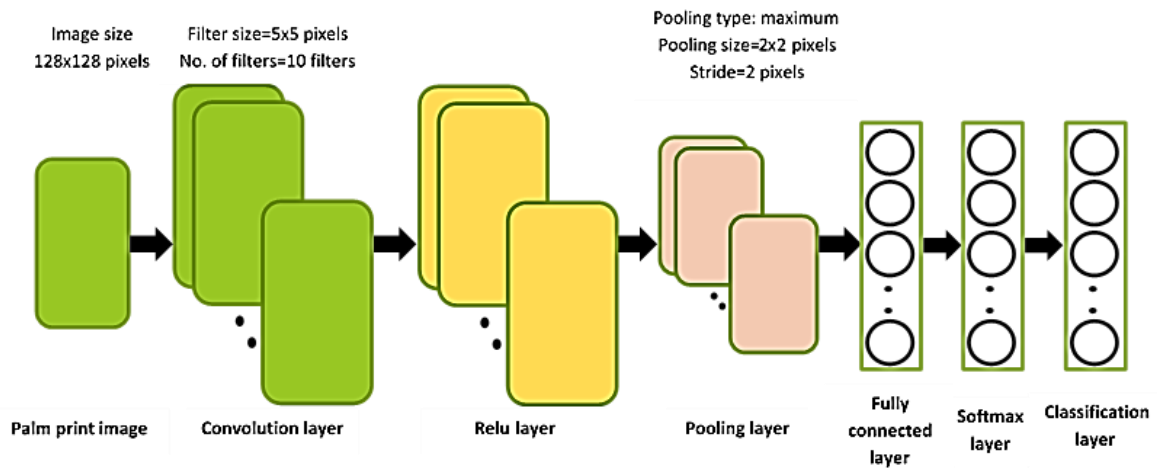


Figure 2. The architecture of the proposed PCNN

3. RESULTS AND ANALYSIS

First of all, a dataset of PolyUC (Version 1.0) is found to be useful. In this dataset, a commercially three-dimensional digitizer device of type Minolta VIVID 910 is exploited to capture three- and two-dimensional hand images. The palm side was considered. 10 images were captured from each participant in two sessions (5 images during each session). A range of 1 week to 3 months was determined as the elapsed time. Users of ages 18 to 50 years old were participated from students and staff, they are of different ethnics and genders. The users were requested to make small changes to their hand positions among the capturing processes. Also, they were required to take off any woreed jewellery or ring. Contactless situation was utilized as friendly collecting samples. Black background and indoor environment were exploited during collecting the hand image samples. Each two-dimensional collected image is of a bitmap format. Each two-dimensional hand image has a resolution of $640 \times 480 \times 3$ pixels. The samples were acquired from so far distance (approximately 0.7 m). Segmented two-dimensional palm print images are offered within the same dataset. Each one of them is an intensity image with the size of 128×128 pixels [42]. Different examples of palm print images from this dataset are presented in Figure 3.

Total of 1000 two-dimensional palm print images from 100 subjects are used in this work. They are partitioned as 700 palm print images for the training and 300 palm print images for the testing. Figure 3 shows different examples of palm print images. The proposed PCNN has been trained for the employed dataset. Training parameters were considered as: 128 mini batch size, 0.0001 weight decay, 0.03 fixed learning rate, 0.9 momentum value, 100 epochs and stochastic gradient descent with momentum optimizer. For specifying

the appropriate PCNN parameters, many experiments were established and examined. Table 1 and Figure 4 show the results of assessing different network parameters.

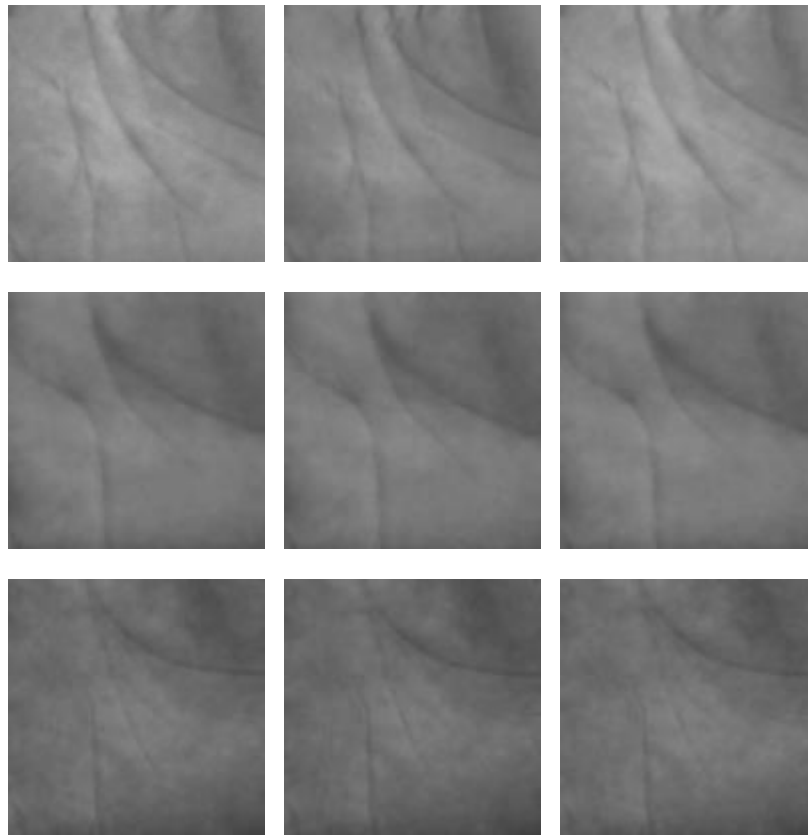


Figure 3. Different examples of palm print images from the dataset of (PolyUC) (Version 1.0) [42]. Each row has samples from a same participant, whereas, each column has different palm print samples

Table 1. The performances of assessing different network parameters

Convolution Layer		Max-Pooling Layer		Accuracy
Filter Size	No. of Filters	Pooling Size	Stride	
3×3	10	6×6	6	95.33%
5×5	10	6×6	6	97%
7×7	10	6×6	6	92.67%
9×9	10	6×6	6	96%
11×11	10	6×6	6	96%
13×13	10	6×6	6	94.33%
15×15	10	6×6	6	92.33%
5×5	2	6×6	6	64%
5×5	4	6×6	6	82.67%
5×5	6	6×6	6	96%
5×5	8	6×6	6	90%
5×5	10	6×6	6	97%
5×5	12	6×6	6	96%
5×5	14	6×6	6	94.67%
5×5	10	2×2	6	94%
5×5	10	4×4	6	94%
5×5	10	6×6	6	97%
5×5	10	8×8	6	96%
5×5	10	10×10	6	94.33%
5×5	10	6×6	2	94.33%
5×5	10	6×6	4	95.33%
5×5	10	6×6	6	97%
5×5	10	6×6	8	95.67%

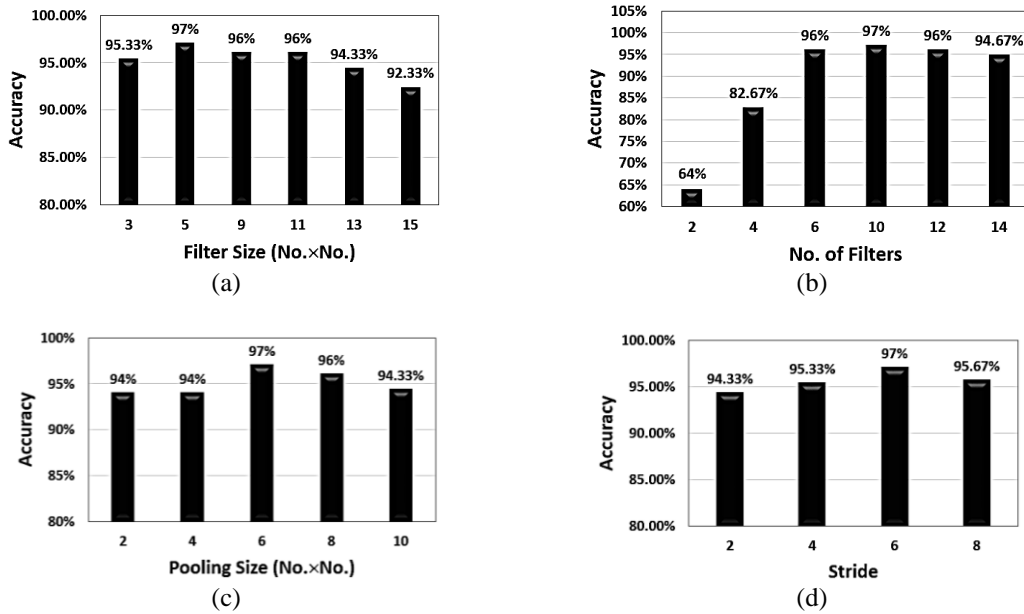


Figure 4. Assessing different network parameters: (a) regulated accuracies for tuning the filter size of the convolution layer, (b) regulated accuracies for tuning the number of filters of the convolution layer, (c) regulated accuracies for tuning the filter size of the max-pooling layer and (d) regulated accuracies for tuning the stride of the max-pooling layer

From this table it can be seen that parameters of convolution and pooling layers are evaluated one after one, by tuning a single parameter and settling the values of other parameters. Then, the best tuned value is considered and assigned in the next round, where another single parameter is examined. The performances can simply be assessed by observing the attained accuracies. It can be investigated that best reported parameters of the convolution layer are 5x5 pixels for the filter size and 10 filters for the number of filters. In addition, it can be seen that best recorded parameters of the max-pooling layer are 6x6 pixels for the pooling filter size and 6 pixels for the stride. These are due to the highest accuracy of 97%, which has been achieved after applying these parameters. By changing a value of any parameter to slightly more or less than the successfully assessed value, the accuracy would be decreased. More experiments have been executed and examined in this study as given in Table 2 and Figure 5.

Table 2. More experiments for changing both the pooling size and stride values the max-pooling layer

Convolution Layer		Max-Pooling Layer		Accuracy
Filter Size	No. of Filters	Pooling Size	Stride	
5x5	10	2x2	2	97.67%
5x5	10	4x4	4	97.33%
5x5	10	6x6	6	97%
5x5	10	8x8	8	95%

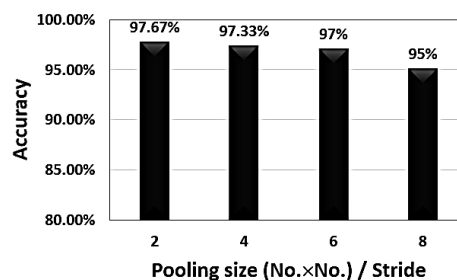


Figure 5. Performances for changing both the pooling size and stride values of the max-pooling layer after applying more experiments

As it can be observed that by tuning both values of pooling filter size and stride, the accuracy has slightly been increased to 97.67%. This accuracy has been obtained by tuning both parameters of pooling size and stride to 2×2 pixels and 2 pixels, respectively. It can be considered as the best verification performance by using the proposed PCNN. It is worth mentioning that the PCNN has also been assessed by using average-pooling type. The accuracy here decreased to 93.67%. Moreover, increasing the PCNN structure by adding more layers of convolution, ReLU and pooling are also explored. By applying two sequential convolution and ReLU layers, the accuracy also decreased to 94.66%. Furthermore, by applying three sequential convolution, ReLU and max-pooling layers, the accuracy further decreased to 85.33%. These performances are obviously less than the best benchmarked accuracy. Therefore, their parameters have been discarded.

4. CONCLUSION

In this paper, a deep learning model called the PCNN was approached. This network was carefully designed. It was adapted for two-dimensional palm print images and it can be used for the verification purposes. Many experiments were applied to examine different parameters of its hidden layers. Its architecture is simple but efficient. It consists of multiple essential layers that are reasonably organized. Its parameter values have been investigated and benchmarked. The best obtaining result showed that a high accuracy of 97.67% has been achieved in the case of palm print verification.

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