Image Anal Stereol 2025;44:49-54 doi: 105566/ias.3409
Original Research Paper

PALMPRINT CLASSIFICATION WITH MULTIPLE FILTER FACES, FOURIER FEATURES AND VOTING TECHNIQUE

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(Received October 6, 2024; revised February 27, 2025; accepted March 17, 2025)

ABSTRACT

In this paper, we propose a novel method for palmprint classification. We extract the central region from the palmprint image, calculate eight filter faces (FF) from the region based on eight pairs of filters, compute the Fourier features from each FF, classify each of them to one known class, and then perform majority voting to determine the final class label of the unknown palmprint image. By examining the structures of the selected filters, we can see that our new method can suppress random noise and at the same time it can extract directional features from the palmprint images. This is the main reason why FF-based methods are better than non-FF-based methods for palmprint classification. In addition, the majority winning policy (voting) based on eight FFs improves classification accuracies significantly. Experimental results demonstrate that our new method outperforms several existing methods for palmprint classification.

Keywords: Fast Fourier transform (FFT); filter faces (FF); majority voting technique; palmprint recognition.

INTRODUCTION

Palmprint classification is a very important topic in computer vision. We briefly review several existing methods for palmprint classification here. Zhang *et al.* (1999) studied two novel characteristics in palmprint verification: Datum point invariance and line feature matching. You *et al.* (2002) analyzed hierarchical palmprint identification via multiple feature extraction. Dong *et al.* (2004) investigated digital curvelet transform for palmprint recognition. Chen *et al.* (2006) performed palmprint classification by dual-tree complex wavelets. Zhang *et al.* (2003) studied on-line palmprint identification in 2003. Trabelsi *et al.* (2022) developed efficient palmprint biometric identification systems with deep learning and feature selection methods. Wu *et al.* (2021) studied triple-type feature extraction for palmprint recognition. Zhao *et al.* (2023) analyzed multiview learning-based generic palmprint recognition. Fei *et al.* (2019) worked on feature extraction methods for palmprint recognition. Alausa *et al.* (2022) surveyed on contactless palmprint recognition system in 2022. Idrissi *et al.* (2020) performed a comparative study on palmprint recognition with state-of-the-art local texture descriptors.

PROPOSED METHOD

In this paper, propose a new method for palmprint classification. We extract the central region from the palmprint images, compute eight FFs from the region according to eight pairs of filters and then calculate the Fourier feature maps from each FF and take the Fourier spectra. We perform classification with the extracted feature maps and then conduct majority voting to determine the final class label of the unknown palmprint image.

We define eight pairs of high-pass filters (HF) and low-pass filters (LF) as follows, where the first four pairs of filters are of size 7×7 and the second four pairs of filters are of size 9×9.

$$HF\{1\} = \begin{pmatrix} -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \\ -1 & -1 & -1 & 0 & 1 & 1 & 1 \end{pmatrix},$$

$$HF\{2\} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{pmatrix},$$

$$HF\{3\} = \begin{pmatrix} 0 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 & -1 & -1 \\ 1 & 1 & 1 & 0 & -1 & -1 & -1 \\ 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{pmatrix},$$

$$HF\{4\} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 1 & 0 & -1 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 & -1 & -1 \\ 1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 0 & -1 & -1 & -1 & -1 & -1 & -1 \end{pmatrix},$$

$$LF\{1\} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix},$$

LF{2}=LF{1},
LF{3}=LF{1},
LF{4}=LF{1},

$$HF\{5\}=\begin{pmatrix} -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & 0 & 1 & 1 & 1 & 1 \end{pmatrix},$$

$$HF\{6\}=\begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{pmatrix},$$

$$HF\{7\}=\begin{pmatrix} 0 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 0 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 1 & 1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 1 & 1 & 1 & 1 & 0 & -1 & -1 & -1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 0 & -1 & -1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{pmatrix},$$

$$HF\{8\}=\begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 0 & -1 & -1 & -1 \\ 1 & 1 & 1 & 1 & 0 & -1 & -1 & -1 & -1 \\ 1 & 1 & 1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 1 & 1 & 0 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 0 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 0 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{pmatrix},$$

$$LF\{5\}=\begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix},$$

LF{6}=LF{5},
LF{7}=LF{5},
LF{8}=LF{5}. (1)

The FF{i}, i ϵ [1,8], can be defined as Chen *et al.* (2018):

$$FF\{i\}(x,y) = \arctan\frac{HF\{i\}*I(x,y)}{LF\{i\}*I(x,y)} \quad (2)$$

where * is the convolution operator, HF{i} is the high-pass filter, LF{i} is the low-pass filter, and I is the palmprint image. It is not difficult to prove that the FF{i}, i ϵ [1,8], are approximately illumination invariant for any LF{i} and HF{i}. We extract the Fourier features from each FF by means of *fft2* available in Matlab and then take the spectra. Fig.1 shows the flow-chart of the proposed algorithm in this paper. We extract eight FFs from the input palmprint image, perform the 2D FFT transform to each FF, classify the palmprint image with the nearest neighbour classifier, and then conduct majority voting to determine the final class label of the unknown palmprint image

We provide the algorithm for training palmprint images here:

1) Read the palmprint image and extract the central region (Fig. 2).
2) Calculate FF{i}, i ϵ [1,8] from the central region.
3) Extract the Fourier features from the FF{i} and take the spectra, denoted as Spec{i}, i ϵ [1,8].
4) Save the features in a database for later query.

We provide the algorithm for testing palmprint images here:

1) Read the palmprint image and extract the central region (Fig. 2).
2) Calculate FF{i}, i ϵ [1,8] from the central region.
3) Extract the Fourier features from the FF{i} and take the spectra, denoted as Spec{i}, i ϵ [1,8].
4) Use the extracted features to query the feature database by the nearest neighbour (NN) classifier. Let us denote the calculated class labels as ID = {idk}, k ϵ [1,8].
5) Conduct majority voting on ID to determine the final class label of the testing palmprint image.
6) Compute the correct classification rate of our new algorithm, which is defined as the ratio between the number of correct classification and the number of total palmprint images.

Our majority voting technique selects the most frequent element in an array as the class label of the unknown palmprint image, which improves the classification accuracy significantly as demonstrated in our experiments. We count the number of times an element in an array occurs and then find the array index corresponding to the value with the most occurrences. Finally, we output the element in the array with most occurrences as the class label of the unknown palmprint image.

We have the following observations about the speed of our new algorithm. We have implemented our new algorithm in unoptimized Matlab code in this paper, so it is a bit slow. We can port it to the faster C++ programming language in the future. In our new algorithm, we select to use eight FFs to extract the feature maps from the palmprint image. Since these FFs are independent of each other, we can implement them in parallel such that faster execution can be achieved. We can also run our new algorithm on Graphics Processing Units (GPUs) so that we can recognize palmprint images even faster.

The computational complexity of our new algorithm can be summarized as follows. The eight FFs can be calculated in O(8MN) operations, where the palmprint image has M×N pixels. The Fourier features can be extracted with O(8MN log(MN)) operations. The NN classifier and the voting technique can be computed in linear time. Therefore, the overall computational complexity of our new method is O(8MN log(MN)).

The main reason why we choose handcrafted features instead of deep learning in this paper is because the number of classes in palmprint recognition can change frequently. When new palmprint classes are available, we need to train the deep learning networks again, which is very time consuming. In addition, the number of palmprints for each class should be large for deep learning, so collecting many palmprint samples is a difficult task. Existing pattern classification problems such as traffic sign recognition and handwritten digits recognition are good for deep learning since the numbers of classes in both problems do not change over time. As a result, handcrafted features such as those proposed in this paper are better suited for our palmprint recognition problem.

The main contribution of this paper is the following. We extract eight FFs from the extracted palmprint central region according to eight pairs of filters. By examining the structures of the selected eight pairs of filters, we can see that they can extract directional features from the palmprint images, and they can suppress random noise as well. This is the main reason why FF-based methods are better than non-FF-based methods for palmprint classification. Furthermore, the majority winning policy (voting) based on eight FFs improves classification accuracies significantly. Our experimental results demonstrate the success of our new algorithm proposed in this paper for palmprint classification.

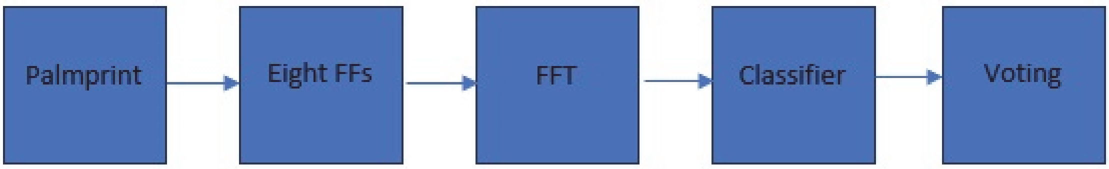

Fig. 1. *The flow-chart of the proposed algorithm in this paper.*

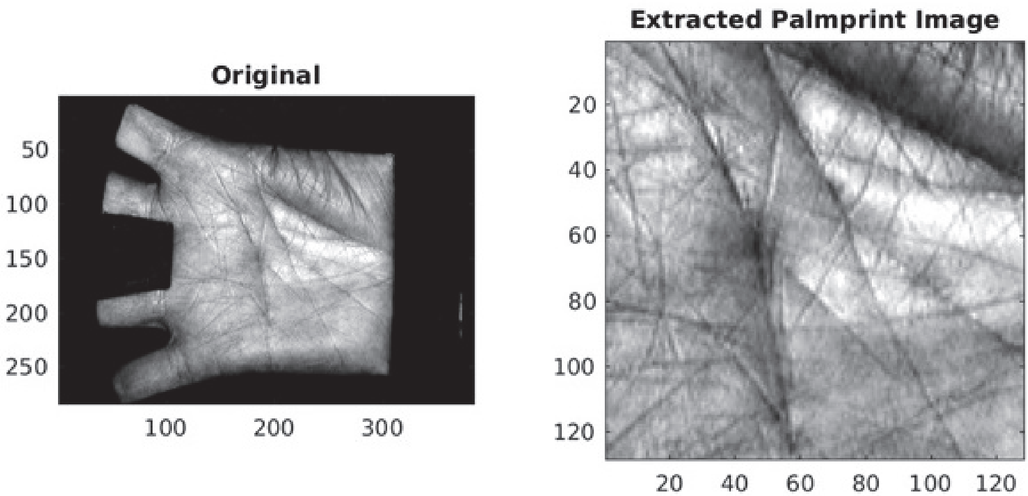

Fig. 2. *Palmprint image and extracted central region.*

RESULTS

We perform experiments for palmprint classification with the PolyU palmprint database, which contains 100 different palms, and each has six samples collected in two sessions. For each palm, we use four of the six palmprint samples for training and the rest of samples for testing. The size of the original palms without preprocessing is of 284×384 pixels. We extract the central region of the palm image for palmprint classification with a size of 128×128 pixels.

We test the effect of additive Gaussian white noise (AGWN) on palmprint classification. We add AGWN to clean palmprint image as follows:

$$B = A + \sigma n\ N(0,1), \tag{3}$$

where B is the noisy palmprint image, A is the noise-free palmprint image, σn is the noise standard deviation, N(0,1) is the normal distribution with zero mean and unit variance. We set the seed of the random number generator to zero so that we can reproduce our experimental results for different runs. We only add noise to testing palmprint samples but not to training samples.

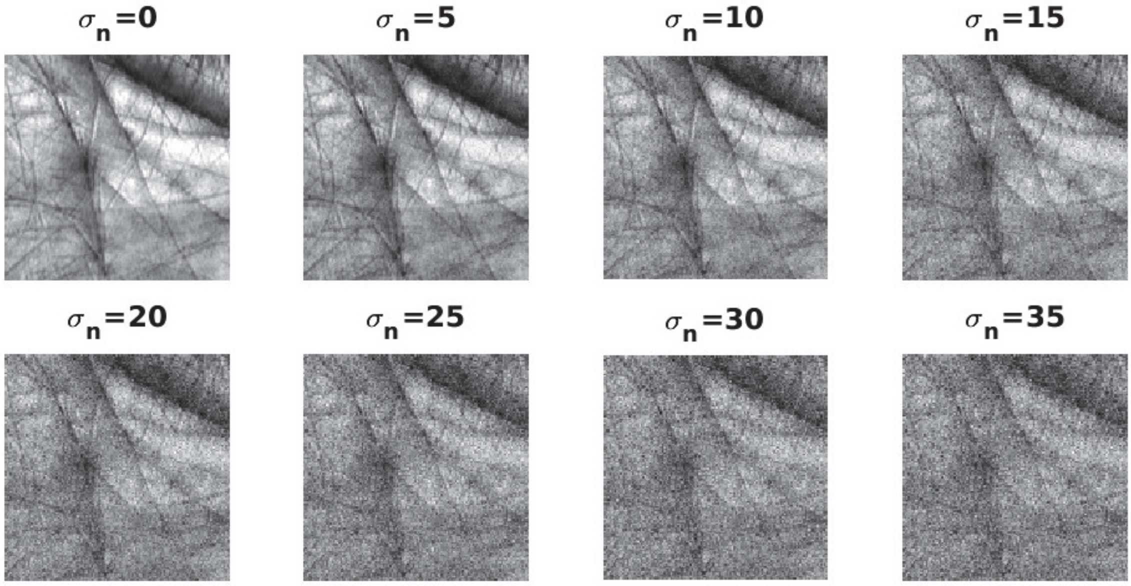

Fig. 3. *Palmprint images with different noise levels (σn=0, 5, 10, 15, 20, 25, 30 and 35).*

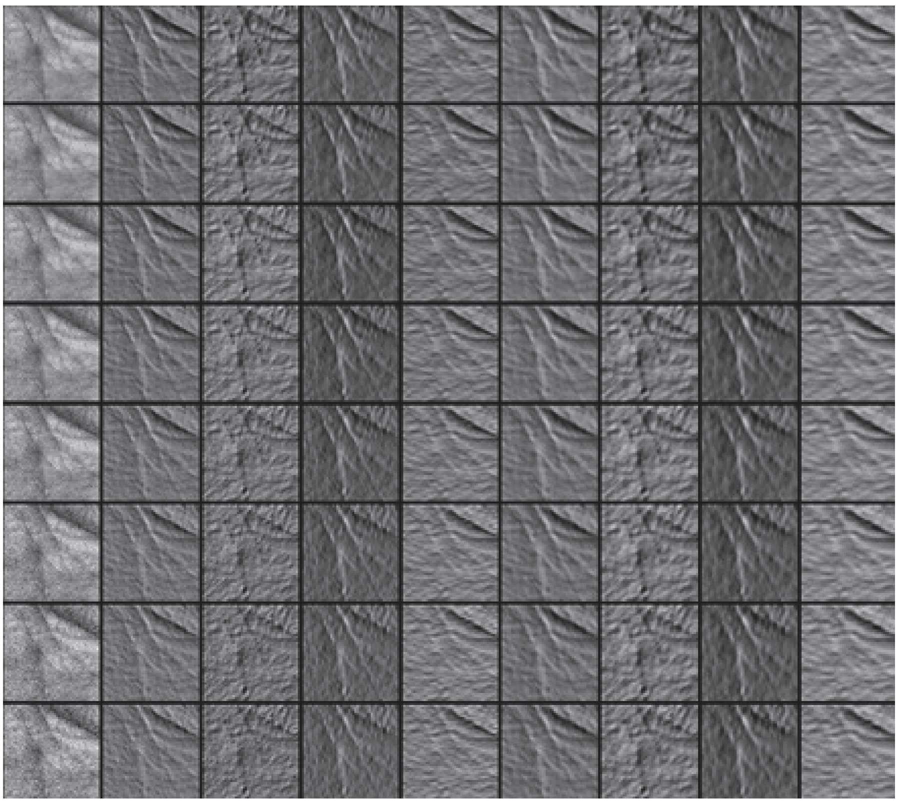

Fig. 4. *Palmprint images (first column), FF{1} (second column), FF{2} (third column), FF{3} (fourth column), FF{4} (fifth column), FF{5} (sixth column), FF{6} (seventh column), FF{7} (eighth column), and FF{8} (ninth column). The first to the last rows correspond to different noise levels σn=0, 5, 10, 15, 20, 25, 30 and 35, respectively.*

Fig. 3. shows palmprint images with different noise levels (σn=0, 5, 10, 15, 20, 25, 30 and 35). In addition, Fig. 4 displays the palmprint images (first column) and their eight extracted FFs (second to last column). The first to the last rows correspond to different noise levels σn=0, 5, 10, 15, 20, 25, 30 and 35, respectively. It can be seen in Fig. 4 that the FFs are very robust to AGWN since the extracted FFs are very clean without showing any noise content in them. This shows that the FFs are good at invariant palmprint classification even when AGWN is present in palmprint images.

Our experimental results with the PolyU palmprint database have the following observations. The best results are highlighted in bold font in both Tables 1 and 2. From Table 1, we can see that our proposed method (98.97%) is better than Zhang and Shu (1999) (93.3%), You *et al.* (2002) (95%), Dong *et al.* (2004) (95.25%), Chen *et al.* (2006) (97%), and Zhang *et al.* (2003) (98%) for palmprint classification. In addition, from Table 2, we can see that the Fourier features are better than the HOG features, the LBP features, and the DWT features for palmprint classification. The major reason why the Fourier features are the best for palmprint classification is because the Fourier spectra are invariant to spatial shifts, which is very important in invariant palmprint recognition. In our experiments, the DWT is chosen as Daubechies-4 wavelet transform. Furthermore, from Table 2, we can see that our method with FF is always better than that without FF for palmprint classification no matter what features (HOG, LBP, DWT and FFT) are used. In addition, the Fourier features combined the FF achieves the best classification results for all noise levels (σn=0, 5, 10, 15, 20, 25, 30 and 35) without exception. This demonstrates the success of our new method proposed in this paper for palmprint classification.

Table 1. *The correct classification rates (%) of different methods for palmprint classification. The best results are highlighted in bold font.*

Zhang and Shu (1999)	You *et al.* (2002)	Dong *et al.* (2004)	Chen *et al.* (2006)	Zhang *et al.* (2003)	Proposed Method
93.3	95	95.25	97	98	**98.97**

CONCLUSIONS

Palmprint classification is a very challenging research topic. In existing literature, many techniques have been proposed to deal with this problem. Nevertheless, there still exists a need to further improve existing methods and propose new ones for palmprint classification.

In this paper, we have proposed a new method for palmprint classification. We extract the central region from the input palmprint image, compute eight FFs from the extracted region based on eight pairs of filters, calculate the Fourier features from each FF, classify each of them to one known class, and then perform majority voting to determine the final class label of the input palmprint image. Experimental results show that our new method performs the best for palmprint classification even if noise is present in the palmprint images.
Future research will be conducted by experimenting with deep convolutional neural networks (DCNN) for palmprint classification. We can also perform a systematic study to compare our new method proposed in this paper with many state-of-the-art methods developed in the past.

Table 2. *The correct classification rates (%) of the proposed method with and without filter faces for different features (HOG, LBP, DWT and FFT) and different noise levels (σn=0, 5, 10, 15, 20, 25, 30 and 35) for palmprint classification. The best results are highlighted in bold font.*

Filter Faces	Features	Noise (σ_n) 0	5	10	15	20	25	30	35
No	HOG	87.63	84.54	74.23	38.14	13.92	5.15	2.06	1.55
	LBP	78.87	13.40	2.58	1.03	1.55	1.03	1.03	0.52
	DWT	62.37	62.37	61.86	61.86	62.37	61.86	62.37	46.91
	FFT	94.85	95.88	94.85	93.30	89.69	75.26	62.37	61.86
Yes	HOG	92.27	89.18	86.60	81.44	73.20	51.03	38.66	23.71
	LBP	97.94	88.14	41.24	11.86	4.64	3.61	2.58	2.06
	DWT	74.23	73.71	72.68	72.16	72.16	72.68	72.68	71.13
	FFT	**98.97**	**99.48**	**99.48**	**98.97**	**98.45**	**97.42**	**95.36**	**90.21**

ACKNOWLEDGEMENTS

Conflict of Interest: The authors declare that they have no conflict of interest.

Data Availability Statement: Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Author Contributions: G.Y. Chen (Coding, writing, validation). A. Krzyzak (Revision, supervision).

Ethics Approval: No ethical approval is required. The authors declare that they have no conflict of interest.

The authors would like to thank the anonymous reviewers for their constructive suggestions and comments, which improve the quality of this paper.

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