Face-Palm Print Recognition System Based On 2d Circular Wavelet Filter And Contourlet Transformation

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Keywords

face recognition, palm print recognition, multi biometrics system, 2D circular wavelet filter, contourlet transformation

Abstract

The study proposes a multimodal biometric design that combines face and palm print recognition modules. To extract the features from the face data set, we proposed a novel 2-D circular wavelet filter that depends on HAAR filters and used the contourlet transformation in palm print data sets. The multimodal biometric design merges the features extracted from different types of unimodal system UBS by using a fusion level. Our proposed approach wants to decrease the time required to recognize a person depending on 2-D CDWT and enhance the accuracy of recognition by using the 2-D CDWT and contourlet transformations as pre-processing level in our approach, then the CNN model is applied to train and test our approach. Our data set was taken from 110 people which means 1100 pairs of images in 10 sessions. This approach's results look good and progressed over other most recent architectures by recording a precision of 99.3%, with a score-level fusion.

Research Article
Submission Date : 20.04.2023
Accepted Date : 28.10.2023

1. INTRODUCTION

The human face has a piece of certain individual key information to identify someone compared with other people in the human community. The eye and brain is the most important part of the human system that can distinguish and analyze each face taking a quick look, so many algorithms are produced to improve a computer-based program for analyzing faces similar to the efficiency of the human system. A lot of ideas and algorithms were suggested by researchers to extract features and make true decisions for classification and discover the person's identity (s, 2023). An interesting algorithm for the biometric system has developed rapidly over the last few decades. This development of applications in the biometric system is gaining attraction among industries like video surveillance, criminal identification, and building access control (Kortli et al., 2020). Researchers tried to add modifications to increase the efficiency of biometric design and theories. The efforts are focused to find a new idea for recognizing humans by using the multi-type of features, so a multimodal biometric system (MBS) has been proposed (Hardalac et al., 2020). The contribution of our approach is to add a new pre-processing tool to enhance the extraction of the spatial and frequency information from the

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input image and then entered the extraction information into the CNN model instead of the image itself and used two types of data set as an MBS instead of UBS. The 2-D CDWT is proposed like 2-DDWT which represents one of the efficient approaches in computer vision because it can extract both the spatial and frequency information of the input signal. Since it possesses several crucial mathematical qualities. in our study, the Haar filter is applied to find the features of the face.

2. REVIEW RELATED WORK

There are many issues and difficulties that appeared against UBS like Noisy data, Non-universality, inter-class similarities, spoof attacks, and intra-class variation. The UBS suffers from a very huge value of both False Acceptance Rate (FAR) and False Rejection Rate (FRR)(Oloyede & Hancke, 2016). So,the researchers suggested The MBS that solves many problems facing the UBS and enhances the model's performance to enhance the criteria like reliability, security, and precision of the system (Leghari et al., 2018).
Channe gowda et.al.(Bc & Prakash, 2022) suggested a multimodal biometric recognition with DWT depending on face and signature data sets. The security solution depending on Discrete Wavelet Transform (DWT) and Multi input data samples model. Mansoura et.al. (Mansoura et al., 2019) depended on Adaptive Score Normalization, PCA, DCT, DWT, and SVD with the Euclidean, distance and applied to Face and Iris Recognition, the recognition rate (98.50%) needs a lot of time to calculate PCA, SVD, and Euclidean, distance. Regouid and et.al. (Regouid et al., 2019) suggested using three types of datasets (ECG, ear, and iris data sets) to recognize the person but increasing the dataset caused to increase in the processing time.So, another type of research tried to suggest a novel method to speed up of execution time of recognizing the human face. Preksha (Singhal & Kumar, 2022) proposed an algorithm to speed up the model by combining Principal Component Analysis (PCA) with Wavelet Transform.
There are many important factors play a key role in choosing the suitable face recognition like: Time required for analysis and the memory space consumed in storage (Agrawal et al., 2021). In our approach, the pre-processing level is using a 2D circular wavelet Filter and Contourlet transformations. However, the fantastic development of deep learning and machine learning in the last few years, make many researchers use the Convolutional Neural Network (CNN) methods to enhance the precision of biomedical theories. A lot of studies into multimodal biometric technologies are described in Table 1 with different datasets and theories.

3. THE PROPOSED BIOMETRIC MODAL

In this study, we proposed an MBS by using face and palm recognition by implementing two sets of images.The Data set which is used in the proposed design consists of images of 110 subjects, each subject has 10 face images and 10 palm print images for different sessions. The basic blocks of our system are described in Figure 1. The pre-processing step in our study consists of a 2-D circular discrete wavelet transform (2-D CDWT) based on the Haar filter. The contourlet transformations are implemented on each palm print image. These operations are applied to every image on the training step.

Table 1. Multimodal systems and Their type of systems algorithm

Model	Year	Biometric used	algorithms
Channegowda AB (Bc & Prakash, 2022)	2022	Face, finger vein, and signature images.	DWT

E. Sujatha (Sujatha & Chilambuchelvan, 2017)	2018	Iris, Palm Print, Face and Signature	DWT
M.Regouid, M. (Regouid et al., 2019)	2019	ECG signal, ear and iris	local descriptors
Nada Alay (Nada Alay, 2020)	2020	Face, Finger Vein, and Iris	Deep Learning
Inass Shahadha (Agrawal et al., 2021)	2020	High-Resolution Palm prints	GLCM
K. Gunasekaran (Tabassum et al., 2022)	2019	face, fingerprint, and iris	Deep learning machine
D.R.Nayak (Tarawneh et al., 2018)	2021	Ear and Face profile	CNN

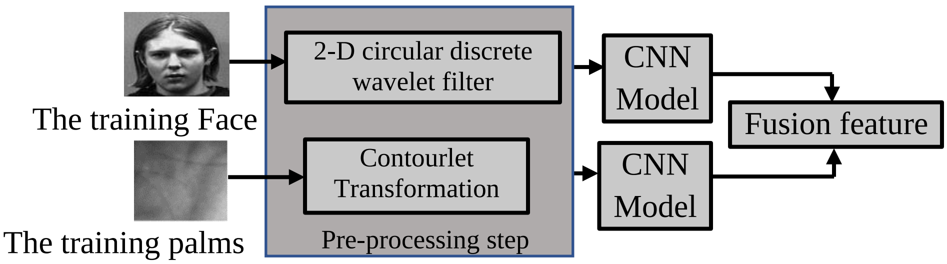

Figure 1. The proposed Multimodal Biometric System**.**

4. THE PROPOSED 2-D CIRCULAR DISCRETE WAVELET TRANSFORM FILTER

This study proposes a 2-D filter based on Digital Spectral Transformation (DST), which is described by (Tarawneh et al., 2018)

$$z^{-1} \xrightarrow{\boldsymbol{DST}} \left(\frac{\boldsymbol{a}+z_1^{-1}}{1+az_1^{-1}}\right)\left(\frac{b+z_2^{-1}}{1+bz_2^{-1}}\right) \tag{1}$$

The 1-D Haar filter is converted into 2-D version by DST as shown in the following equations:

$$H_0(z) = \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} \tag{2}$$

$$\because H_0(z) = \frac{1}{\sqrt{2}}(1+z^{-1})$$

$$\begin{aligned} \mathrm{H}_0(\mathrm{z}_1,\mathrm{z}_2) &= \frac{1}{2}\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\left(\frac{\mathrm{b}+\mathrm{z}_2^{-1}}{1+\mathrm{b}\,\mathrm{z}_2^{-1}}\right)\right)\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\left(\frac{\mathrm{b}+\mathrm{z}_2}{1+\mathrm{b}\mathrm{z}_2}\right)\right) * \frac{1}{2}\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\right)\left(1+\left(\frac{\mathrm{b}+\mathrm{z}_2^{-1}}{1+\mathrm{b}\,\mathrm{z}_2^{-1}}\right)\right) \\ &= \frac{1}{4}\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\left(\frac{\mathrm{b}+\mathrm{z}_2^{-1}}{1+\mathrm{b}\,\mathrm{z}_2^{-1}}\right)\right)\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\left(\frac{\mathrm{b}+\mathrm{z}_2}{1+\mathrm{b}\,\mathrm{z}_2}\right)\right)\left(1+\left(\frac{\mathrm{a}+\mathrm{z}_1^{-1}}{1+\mathrm{a}\,\mathrm{z}_1^{-1}}\right)\right)\left(1+\left(\frac{\mathrm{b}+\mathrm{z}_2^{-1}}{1+\mathrm{b}\,\mathrm{z}_2^{-1}}\right)\right) \end{aligned} \tag{3}$$

The coefficients of 2D filter (a and b) are chosen to be 0.5. The 2-D CDWT provides three contributions: (1) Reduce the Dimensionality. (2) Data approximation can be specified by Multi-resolution analysis. (3) Feature extraction is more sensitive than other method (Singhal & Kumar, 2022).

5. CONTOURLET TRANSFORM

The contourlet transformation is used in many applications of image processing to calculate and determine the feature extraction effectively and more efficiently than DWT due to the multi resolution analysis. The contourlet transformation is applied to plam- print data to preserve the detail of images and give a high resolution results. The contourlet transform has five characteristics that make it more compact and efficient than the DWT: Multi level of resolution, Localization, The critical value of sampling, Directionality, Anisotropy (Wang et al., 2018).

6. THE CONVOLUTIONAL NEURAL NETWORK (CNN) MODEL

To apply the suggested our MBS by utilizing two traits (face, and palm print), the UM is built at first for each of input dataset then the output of each model is fused by using score level fusion as displayed in Figure 1. The CNN architecture in our design are built by multi-level of CONV2D layer as shown Table 2. The proposed MBS is built to increase the recognition accuracy in the design, simultaneously, enhancing the confidence system by applying different types of datasets as face, and hand patterns.

Table 2. The structure of CNN model in the proposed model

Layers	Configuration	Output size
input	1x 128x128	1x128x128
Conv2-D	16_3x3_st.0_pad 0, BN, Relu	16x128x128
Max pooling	2x2, st.2	16x64x64
Conv2-D	32_3x3_st.0_pad 0, BN, Relu	32x64x64
Max pooling	2x2, st.2	32x32x32
Conv2-D	32_3x3_st.0_pad 0, BN, Relu	32x32x32
Full1	2048	2048
Full2	2048	2048
Full2	256, SoftMax	256

7. FEATURE FUSION MODEL

Two sets of features are used in the proposed method which are concatenated into a single one with more discriminative power than either of the input function vectors using the fusion features model to determine whether the outputs fit or not. The feature-level is applied by using concatenation, summation, product, weighted, experimental and maximum method. In this study, summation method is chosen (Bai et al., 2018).

$$Z_1 = X^* + Y^* = W_x^T\, X + W_y^T\, Y = \begin{pmatrix} W_x \\ W_y \end{pmatrix}^T \quad (4)$$

8.RESULTS AND DISCUSSIONS

The system is implemented using Keras Python library for implementing the proposed model and run the code under GeForce RTX 3060 NIVIDIA GPU's. The data sets contain of face images and palm print image for 110 persons. The total sample images for training are 8800 pairs of images; 8800 (1100*8) for face images and 8800 images for palm print to train the model and the 22000 (11000*2) face data, 220(110*2) palm print data for validation and testing model.

Our suggested model displayed promising and reasonable results compared with the other researches. The incorporation of utilizing the 2-D CDWT and Contourlet technique shows significant results displayed in Table 3. The proposed technique also improved the accuracy rates. Although (Nada Alay, 2020)reach 100% accuracy rate but this approach used three type of data and this is needing a lot of memory space and more time for training deep model. So, our approach can perform an acceptable accuracy rate with only two types of data.

Table 3. Compare the result of our model with other MBS approaches

References	dataset	subject	Accuracy
(Bc & Prakash, 2022)	Face dataset, finger vein, and signature (ULBP)	40 subjects and 400 samples	92.5%
(Bc & Prakash, 2022)	Face dataset, finger vein, and signature (HOG)	40 subjects and 400 samples	95.8%
(T., 2021)	Palm print, face, Iris, finger print, and vein	--------------	94%
(Nada Alay, 2020)	Face, finger vein, and Iris dataset	SDUMLA-HMT dataset	100%
Our method	Face and palm print	110 subject and 10 sessions	95.39%
		520 subject and 10 sessions	99.3%

9. CONCLUSIONS

MBS depending on face and palm print data set are proposed. This research is considered the first one uses the 2-Dcircular wavelet filter in a MBS to decrease the time required for recognition and enhance the system performance. The data set consist of 1100 subjects. Each subject represents a pair of images, one image is face data and other image is palmprint data.

10. FUTURE WORK

In the future, we intend to do further studies to extend the proposed code by using three data sets aiming at increasing the verification and the security of the system, we can extend our approach and use another trait like finger vein.

Contribution of Authors

This paper presented a novel method based on using the 2D circular filter and countorlet transform as a preprocessing step of deep learning face recognition model. This modification enhanced the deep learning model to extract the most proper features and increase the accuracy of the system.

Conflict of Interest

There is no confliect of interest.

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