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Comparison the Accuracy to Extract Features in Finger Veins and Fingerprints

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Abstract

The biological materials, mostly the images of organs or tissues are needed for biometric recognition like faces, iris, fingerprints and finger veins, as a personal information and the features vary a lot for different people. As a kind of biometric recognition, fingerprints identification has been used widely in our daily life, it can be used on locks, phones or attendance machines. Meanwhile the finger vein identification has become more and more popular. Finger vein collectors are based on infrared imaging like many fingerprints collectors, this paper focus on which one is more accurate, and finding out any approach to improve the accuracy of newly-developing technology finger vein identification.

Keywords

Fingerprints Recognition; Finger Vein Recognition; Image Feature Detection; CNN.

1. Introduction

Biometric recognition refers to the automatic recognition of individuals based on their physiological and / or behavioral characteristics [1], as an approach of personal authentication, is an emerging signal processing area focused on increasing security and convenience of use in applications where users need to be securely identified [2].

The unified design variable is needed when compare, which is basic in the whole experiment, especially for data collection and processing, structure design. Firstly the data used in the experiment is images of biological materials, as mentioned above, the process of collecting is not open enough, the facilities used to collect data are unchangeable, otherwise there can be more variables, as a result, it is the best way to collect data on my own. At the same time, the batch processing is also needed to control the number of variables. The preconditioning of images for biological materials plays a significant role in the data processing, the methods are required to extract the corresponding parts of images where the features are integrated and are easy to extract to train the model. Secondly it is normal for different structure has different performance, the only solution is to choose a suitable structure and never change it.

Fingerprints identification has been used widely in our daily life, it can be used on locks, phones or attendance machines. Meanwhile the finger vein identification has become more and more popular. Finger vein collectors are based on infrared imaging like many fingerprints collectors, which one is more accurate, and is there any approach to improve the accuracy of newly-developing technology finger vein identification.These are the 2 topics of my research this time.

Only convolutional neural networks (CNN) is used in this experiment, which makes it easy to compare the test accuracy and draw a conclusion. Convolutional neural network is different than a regular neural network in that the neurons in its layers are arranged in three dimensions, which allows

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the CNN to transform an input volume in three dimensions to an output volume, so it is always used in image recognition. The images of fingerprints and finger veins are required this neural network to analyse. The training set and testing set should be distributed designedly, which can reflect the accuracy difference between fingerprints identification and finger vein identification, and different approaches should be compared as well to find out a more accurate recognition way, the different approaches are 1) ROI(region of interesting) of finger veins, 2) two finger veins are used to identify simultaneously.

2. Method

By using biometric recognition, it is possible to confirm or establish an individual's identity based on "who she is", rather than by "what she possesses" (e.g., an ID card) or "what she remembers" (e.g., a password)[1], which means extracting features of images for fingerprints and finger veins is the key point in fingerprint and finger vein identifications.

Fingerprints have been used in forensic investigations for the identification of individuals since the late 19th century. However, it is now clear that fingerprints can provide significantly more information about an individual[3]. The fingerprints have different features for different people, it is why fingerprints can be used to identify people, but the size of fingerprints and position in the collectors are changeable, the solution is to find out the specific parts which are easy to extract features.

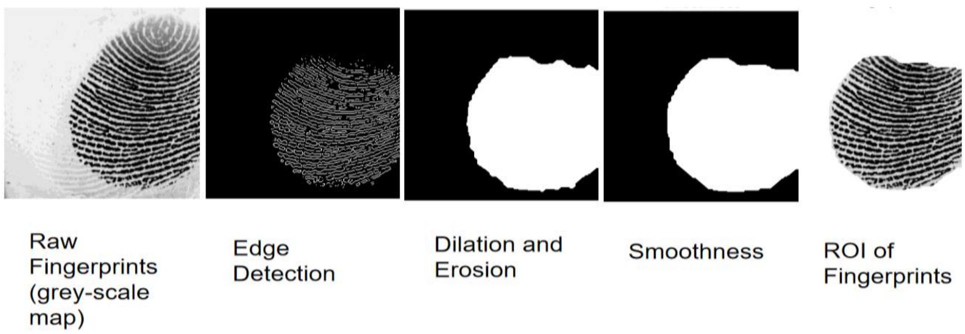

Figure 1: Process of fingerprints preconditioning

As Figure1 shows, the first work is to transform fingerprint images to grey-scale maps, secondly detect the edge, thirdly dilation and erosion, gray scale dilation, erosion and consequently hit-miss transform, are solutions to a regularization problem [4], For positive d, P(d) is the set P enlarged by dilation by a sphere of radius d, and for negative d, P(d) is the set P diminished by erosion by a sphere of radius d, the concepts of dilation and erosion belong to'mathematical morphology' [5], in a word, dilation is to enlarge the bright area, erosion is to enlarge the dark area, when they get balanced, the interference characteristics can be decreased. Fourthly smoothness, it is the open operation, which remains the area, weakens the narrow parts and very thin protuberance. Finally returns the value.

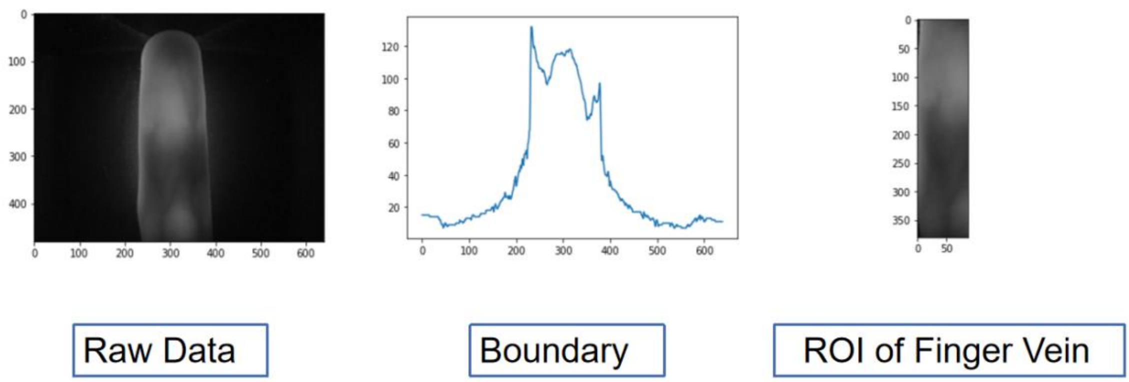

Figure 2: The process of finger vein ROI segmentation

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Finger vein can be considered more secured compared to other hands based biometric traits such as fingerprint and palm print because the features are inside the human body[6]. It is a safer way for finger vein identification because the images can not acquire outside a body while fingerprints can be easily acquired outside a body, and the finger vein acquisition is not affected by the environment like the surface humidity of fingers.

The X-axis in the second picture of Figure2 is length of the finger vein image, the Y-axis is the grey level. The key point is to find out 2 peaks as boundaries, the approach is called hill climbing algorithm. 2 points always returns the highest level nearby in the processing of moving forward, it is easy to find the peaks.

CNN has been proved very successful in solving image classification problems. Research works based on CNN significantly improved the best performance for many image databases, including the MNIST database, the NORB database and the CIFAR10 dataset. It is very good at learning the local and global structures from image data. General image objects like hand written numbers or human faces have obvious local and global structures, hence simple local features such as edges and curves can be combined to become more complex features such as corners and shapes and eventually the objects[7]. The images of fingerprints and finger veins are similar to hand written numbers and human faces the local and global features are needed to extract, because the regions of interests can be anywhere on the 2D plane. CNN can help to deal with the position change.

3. Experiment

For this experiment, a FM10A fingerprint sensor made by the company of Tiancheng, a CP2102 model which is used to transform TTL connector to USB connector, and a corresponding software used to test on upper system created by the same company are used to collect my fingerprint data set and I also used a finger vein data set called FV-USM[8]. These biological materials are very private, in consideration of the universal use of right hand fingerprints in identification on phones, only the volunteers' left hands are used to collect these data set. For these databases, the images were collected from 12 volunteers, the age of the subject ranged from 19 to 52 years old, every subject provided 2 fingers: index and middle fingers. It is also important to finish the process of preconditioning, which means extract the valid part of the collected images. The collected raw data can be used as database images after preconditioning.

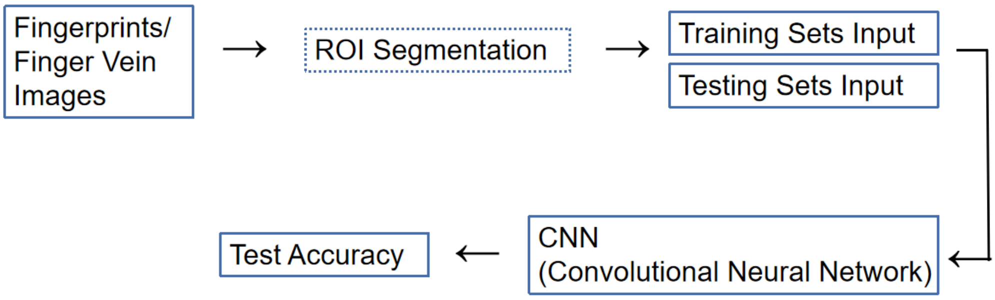

Figure 3: Framework of total experiment

As Figure3 represents, the whole process includes preconditioning, organizing the training and testing sets, choosing the appropriate model to train and test. The test accuracy is to verify whether the identification method is reliable or not.

3.1 Training sets/Testing sets

First of all, there can not be any overlap and the subjects in training sets are set to triple that of testing sets. I designed 5 different conditions to compare: 1) Index Fingerprints, 2) Raw Data of Index Finger Vein, 3) ROI of Index Finger Vein, 4) ROI of Middle Finger Vein, 5) ROI of Index and Middle Finger Vein. Raw data in condition No.2 means the finger vein image has not been extracted ROI.

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Testing accuracy in condition No.1 and No.2 can tell the reliability between fingerprints and finger veins. Testing accuracy in condition No.2 and No.3 can tell the importance of extracting ROI of biological materials images. Testing accuracy in condition No.3, No.4 and No.5 can tell whether using two finger veins to identify simultaneously can improve the accuracy or not.

3.2 CNN structures

Table 1: Network Architecture When the Data of Index Fingerprints are used as Training and Testing sets

Convolution Layer	Input: (None, 64, 64, 1)
	Output: (None, 62, 62, 16)
Max Pooling Layer	Input: (None, 62, 62, 16)
	Output: (None, 31, 31, 16)
Convolution Layer	Input: (None, 31, 31, 16)
	Output: (None, 27, 27, 32)
Max Pooling Layer	Input: (None, 27, 27, 32)
	Output: (None, 13, 13, 32)
Flatten Layer	Input: (None, 13, 13, 32)
	Output: (None, 5408)
Dense Layer	Input: (None, 5408)
	Output: (None, 512)
Dense Layer	Input: (None, 512)
	Output: (None, 12)

As the Table1 shows, the layers are designed logically and when the data of index finger veins are used, as the architecture in Table2, the structures in both cases are the same.

Table 2: Network Architecture When the Raw Data of Index Finger Veins are used as Training and Testing sets

Convolution Layer	Input: (None, 64, 64, 1)
	Output: (None, 62, 62, 16)
Max Pooling Layer	Input: (None, 62, 62, 16)
	Output: (None, 31, 31, 16)
Convolution Layer	Input: (None, 31, 31, 16)
	Output: (None, 27, 27, 32)
Max Pooling Layer	Input: (None, 27, 27, 32)
	Output: (None, 13, 13, 32)
Flatten Layer	Input: (None, 13, 13, 32)
	Output: (None, 5408)
Dense Layer	Input: (None, 5408)
	Output: (None, 512)
Dense Layer	Input: (None, 512)
	Output: (None, 12)

The structure varies when the data of ROI of finger veins are used, because the pixels of finger vein images have changed due to image cut in the process of extracting ROI, the shape of images is different from that in the first two cases, the solution is to reshape the images to different size and import them to the input of new architecture shows in Table3, however, besides the size of input, there is scarcely any other differences in No.3 and No.4 conditions as No.1 and No.2 conditions, which means ROI of index finger vein and middle finger vein are respectively used.

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Table 3: Network Architecture When ROI of Index Finger Vein and Middle Finger Vein are Respectively used as Training and Testing sets

Convolution Layer	Input: (None, 68, 68, 1)
	Output: (None, 66, 66, 16)
Max Pooling Layer	Input: (None, 66, 66, 16)
	Output: (None, 33, 33, 16)
Convolution Layer	Input: (None, 33, 33, 16)
	Output: (None, 29, 29, 32)
Max Pooling Layer	Input: (None, 29, 29, 32)
	Output: (None, 14, 14, 32)
Flatten Layer	Input: (None, 14, 14, 32)
	Output: (None, 6272)
Dense Layer	Input: (None, 6267)
	Output: (None, 512)
Dense Layer	Input: (None, 512)
	Output: (None, 12)

Last but not the least, a numerical example, using a simple concatenated coding scheme, provides a vehicle for explaining how error performance can be improved when soft outputs from the decoders are used in an iterative decoding process[9]. In case No.5, the features in both of index and middle fingers are used to train the model, the concatenated structure as Table4 shows is used to improve the error performance, the test accuracy can tell whether it is valid.

Table 4: Network Architecture When both of ROI of Index Finger Vein and Middle Finger Vein are used as Training and Testing sets

	Samples of ROI of Index Finger Vein	Samples of ROI of Middle Finger Vein
Convolution Layer	Input: (None, 68, 68, 1)	Input: (None, 68, 68, 1)
	Output: (None, 66, 66, 16)	Output: (None, 66, 66, 16)
Max Pooling Layer	Input: (None, 66, 66, 16)	Input: (None, 66, 66, 16)
	Output: (None, 33, 33, 16)	Output: (None, 33, 33, 16)
Convolution Layer	Input: (None, 33, 33, 16)	Input: (None, 33, 33, 16)
	Output: (None, 29, 29, 32)	Output: (None, 29, 29, 32)
Max Pooling Layer	Input: (None, 29, 29, 32)	Input: (None, 29, 29, 32)
	Output: (None, 14, 14, 32)	Output: (None, 14, 14, 32)
Flatten Layer	Input: (None, 14, 14, 32)	Input: (None, 14, 14, 32)
	Output: (None, 6272)	Output: (None, 6272)
Dense Layer	Input: (None, 6267)	Input: (None, 6267)
	Output: (None, 512)	Output: (None, 512)
Dense Layer	Input: (None, 512)	Input: (None, 512)
	Output: (None, 12)	Output: (None, 12)
Concatenate Layer	Input: [(None, 12), (None, 12)] Output: (None, 12)	

The shape of output can not change, the additional layer combines the model when ROI of index and middle finger veins are respectively used, the method is considered to improve the performance of this model when samples are limited.

In summary the total results are in Table5.

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Table 5: Results When Different Samples are used as Training and Testing Sets

Different Training and Testing Sets type	Test accuracy
Data of Index Fingerprints	86.11%
Raw Data of Index Finger Vein	88.89%
ROI of Index Finger Vein	97.22%
ROI of Middle Finger Vein	94.44%
ROI of Index and Middle Finger Vein	100%

The lowest test accuracy occurs when the data of index fingerprints are used as training and testing sets, while ROI of index and middle finger veins can get the highest test accuracy.

4. Conclusion

Comparing the test accuracy with each condition, some conclusions can be easily drawn.

Firstly, as the test accuracy when raw data of index finger veins are used is a little higher than fingerprints of the same finger are used as training and testing sets, it is easier to extract features of finger vein than that of fingerprints. It is even the raw image of index finger vein. As a same finger and the same framework, the features can be extracted more accurately in the case of finger vein.

Secondly, from 88.89% to 97.22%, the test accuracy has improved a lot when ROI of index finger veins are used comparing with the raw data of same fingers are used. Extracting ROI plays an important role in finger vein recognition. As a same finger and the only difference is whether the image of finger vein has been extracted ROI or not.

Finally, the test accuracy is not so different when ROI of index finger veins are used from ROI of middle finger veins are used, it is obvious that it can really improve the accuracy by a combination of 2 different finger veins. The test accuracy even reaches up to 1 when it combines 2 different finger veins to identify, but each of the finger veins can not achieve the good result.

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