Segmentation of fingerprint images using the simplest neural networks

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Abstract. Segmentation of fingerprint images is one of the most important problems in automated fingerprint identification system (AFIS). Segmentation is used to separate the area of the fingerprint (foreground) from the background and areas that cannot be recovered. We propose a new algorithm for fingerprint segmentation based on simplest neural networks, binary region labeling technique, and morphological image processing. This approach was tested on public fingerprint dataset provided by Fingerprint Verification Competition (FVC) 2002. The experimental results showed an impressive accuracy was obtained: FAR 2.4%, FRR 1.1% with per-pixel comparison with the reference.

Keywords: fingerprint images, segmentation algorithm, neural networds.

1. Introduction

Identification by fingerprints is the most commonly used biometric technology [1]. Under the fingerprint in such systems (Fig. 1, left) is meant a specialized grayscale image.

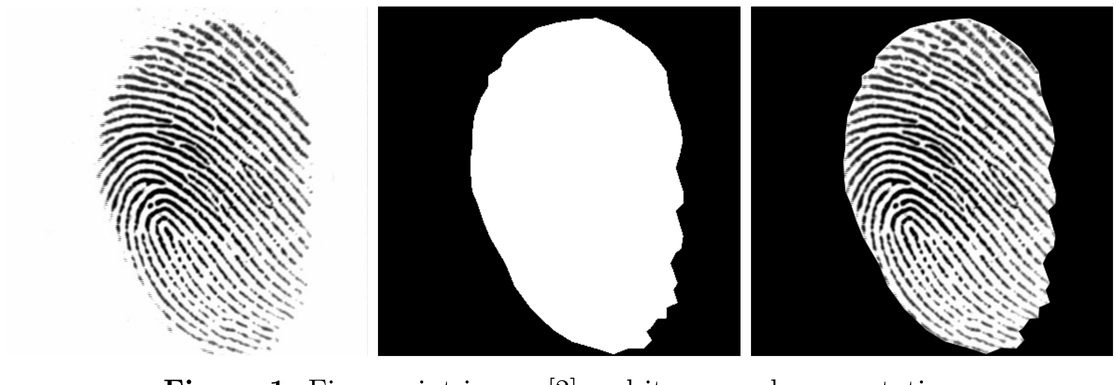

Figure 1. Fingerprint image [2] and its manual segmentation.

In the process of identification, the image of the fingerprint is subjected to several stages of preprocessing [3]. The first is segmentation. The segmentation step is designed to separate the area of the fingerprint (foreground) from the background area and non-recoverable regions. Accurate segmentation can significantly reduce the computational costs of the entire identification, and also discard many false features. For example, the use of segmentation allows more accurately determine locations and types of singular points of the analyzed images (figure 2). Also, segmentation is necessary at the stage of fingerprint image enhancement [4], and at the stage of final identification [5]. Segmentation of fingerprint images was studied in numerous papers. Thus, in [6], a two-stage segmentation algorithm was proposed. At the first stage, a linear classifier was trained in the feature space of 3 dimensions: coherence, average intensity value and its variance. At the second stage, to improve preliminary segmentation results the authors employed standard morphological processing procedure [7]. Training was carried to on DB1B fingerprint dataset offered to participants of Fingerprint Verification Competition (FVC 2000) [8]. Although, the algorithm performs well at this dataset (avg. error is 6.8%), its overfitting is high, since test error obtained on dataset DB2B is 14.3%. The article [10] proposed combined method of segmentation of fingerprint that uses fingerprint orientation field and statistical information of the image. Unfortunately, this paper like some others (see, e.g. [11]) provide either poor verifiable numerical evaluation results or no experimental results to compare at all.

Contribution of this short paper is two-fold. On the first hand, we try to provide fingerprint image segmentation neural-based technique augmented by fully reproducible numerical evaluation. All fingerprint images used in the training and testing stages are taken from the public FVC2002 repository. Source code of our algorithms, manually segmented images employed to experiments as a golden standard, and the final evaluation results can be accessed by the following link https://github.com/PasynkovMK/ITNT_2018.

On the second hand, we try to minimize complexity of the neural networks used for fingerprint images segmentation. In [17], we presented our recent numerical results, where, for fingerprint images segmentation, we trained convolution neural networks optimizing their architecture by local search heuristics. Although the networks obtained performed well providing high quality segmentation on testing datasets, they remain too space expensive to employ on board. Time consumption of these networks also remains high, especially at the training stage.

Therefore, in this paper, we try to examine the extremely bare-bone networks, namely just simple feedforward perceptrons with a single hidden layer. Besides decreasing of time and space consumption, we are motivated to experiments with such networks by the following theoretic reason: these simple networks, with relatively small amount of trainable parameters should suffer much less from the overfitting then their full-blown multiple-layer counter-parts.

The rest of the paper is structured as follows. In Section 2, we provide a general scheme of the algorithm proposed. In Section 3, we discuss the network architecture examined and present the numerical results obtained. Finally, in Section 4, we come to conclusion on applicability of the networks examined to the segmentation of fingerprint images.

2. Algorithm

The proposed algorithm in this paper consists of a simplest neural network, binary region labeling technique and morphological processing. The structural scheme of the proposed algorithm is shown in Fig. 3.

The initial stage of the algorithm is the use of a fully connected neural network. The neural network will be trained to classify isolated individual areas of the image. In this approach uses the size of the area (in our case area size = 11). and the size of the block (in our case block size = 7). The area is the image part, which is fed to the input of the neural network. At the output of the neural network will be a binary output that classifies this area. The classification result fills the center of the given area, corresponding to the size of the block. The illustration is shown in figure 4. Thus, the image of the fingerprint is divided into overlapping areas, with a step of offset in the block size. As a result of this approach, by sequentially classifying each area, we fill the appropriate block on the binary segmentation mask.

At the second stage the results are refined by the known [12] Region Labeling (RL) algorithm.

Figure 2. Finding singular points with segmentation (right) and without it (left). The green dots are the cores, and the red ones are the deltas.

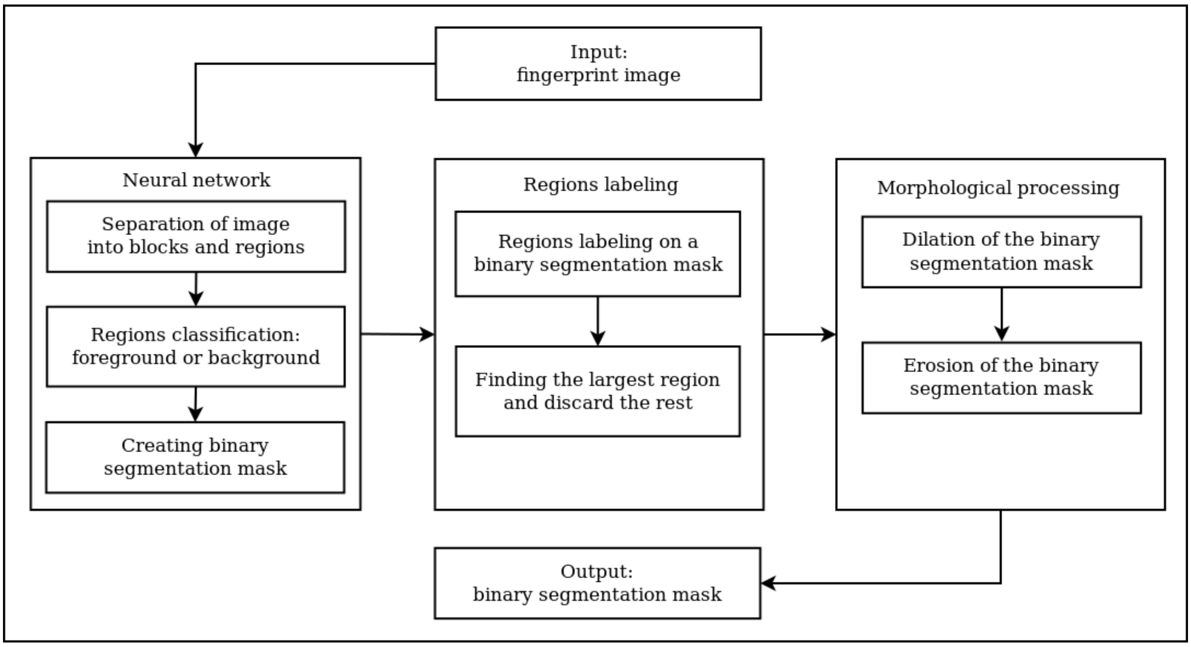

Figure 3. Structural scheme of the algorithm.

Its main idea employes the fact that the vast majority of the fingerprint images contain single connected foreground area. Assuming that true foreground area is the biggest one, other areas can be eliminated by the classic non-recursive algorithm for sequential region labeling.

At the final stage the analyzed image is subjected to Morphological Processing (MP). The combination of the sequential application of dilatation and erosion is called the closing operation. It allows us to get rid of breaks of a certain size. As a result of applying the dilatation to the binary image, we expand the foreground area, thus getting rid of discontinuities of a certain size. And the subsequent application of erosion to the binary image, we restore the original shape of the foreground area already without gaps.

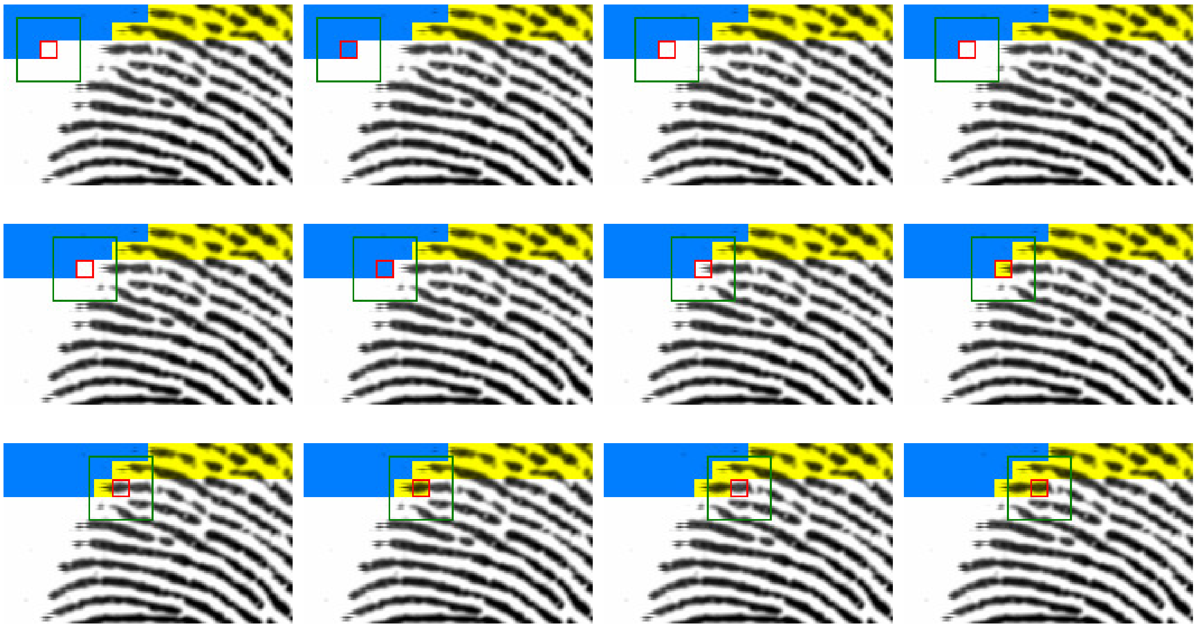

Figure 4. Sequential classification by a neural network.

3. Neural network

Since one of the goals of segmentation is to reduce the computational load by isolating only the informative part of the image, we purposefully investigated the simplest neural networks trying to minimize the number of network parameters [13]. Since, the smaller the number of parameters, the faster the neural network will work.

The use of sequential analysis of small areas of the image by the same neural network has significantly reduced the number of parameters. Thus, we obtained one of the most important advantages of convolutional neural networks - an analog of the convolution operation [14,15].

After that, a study was conducted, the purpose of which was to identify the optimal number of neurons. The criterion of optimality was the criterion of Akaike (AIC) [16]. This criterion fines network for excessive number of parameters. This allows not only to reduce the error, but also to take into account the cost of its reduction.

The work used shared fingerprint images from the Fingerprint Verification Competition (FVC) 2002 competition. The database of the fingerprints of the competition consists of 4 sets of images taken from different types of sensors and having a different resolution. In each set there are 80 images taken from 10 different fingers by 8 examples for each.

During the experiments, each set of fingerprint images was divided into 3 parts. The first part is used for training a neural network and consists of all the fingerprints of any 8 fingers. Thus, the first part consisted of 64 images of fingerprints.

After that, all the images were divided into areas with a step of displacement in the block size. Also, in order to increase the amount of training data, a rotate of these areas was carried out, which made it possible to increase it fourfold.

Other 8 fingerprints belonging to the same finger and not included in the data for training compile a set for checking the neural network during training. The remaining eight prints were used in calculating the final segmentation errors. Thus, when calculating the final segmentation error, previously unused data was used. And thanks to the circulation of training, checking and validation data, an average score was obtained for all fingerprint sets from the FVC 2002 contest.

It was revealed that a network with 6 neurons is the most effective. The graphs of the dependencies are shown at Fig. 5 and 6.

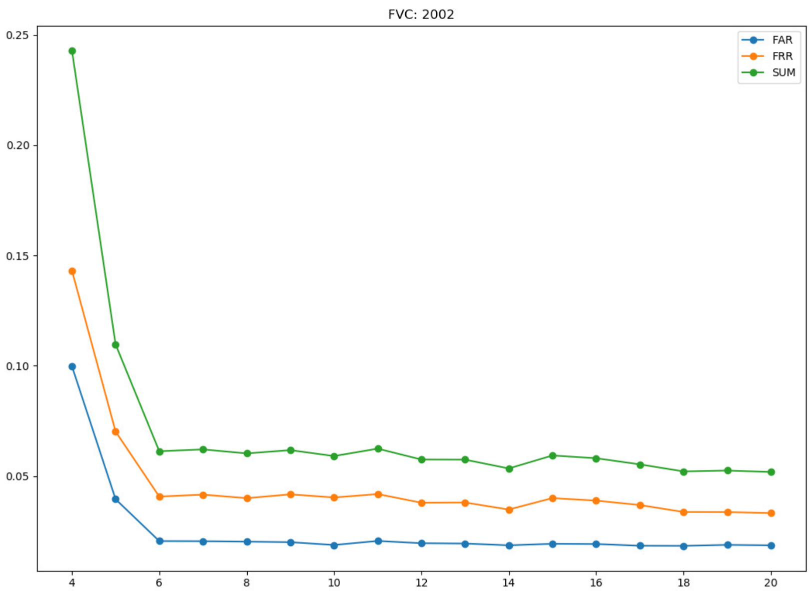

Figure 5. Dependence of the error (vertically) on the number of neurons (horizontally).

Wherein the number of parameters depends on the number of neurons both:

$$parameters = areasize * areasize * n_1 + n_1 + n_1 * n_2 + n_2$$

where, n_1 - number of neurons in the layer 1, n_2 - number of neurons in the output layer. In our case, with the optimal number of neurons is 6, the number of parameters is equal to 746.

It was revealed that a network with 6 neurons is the most effective. After determining the optimal number of neurons, a multi-start is performed and the algorithm is complemented by binary region labeling technique and morphological processing.

To assess the segmentation quality, we use relative pixel-wise difference between algorithm segmentation and manual segmentation:

$$FAR = (manual = 0, algorithm = 1)/N$$

$$FRR = (manual = 1, algorithm = 0)/N$$

where, N is the total number of pixels in the image. The results are given in the table 1.

4. Conclusion

The proposed algorithm showed high efficiency in the segmentation problem of fingerprint images. Thanks to the use of neural networks, the region labeling algorithm and morphological processing, FAR 2.478%, FRR 1.153% were achieved.

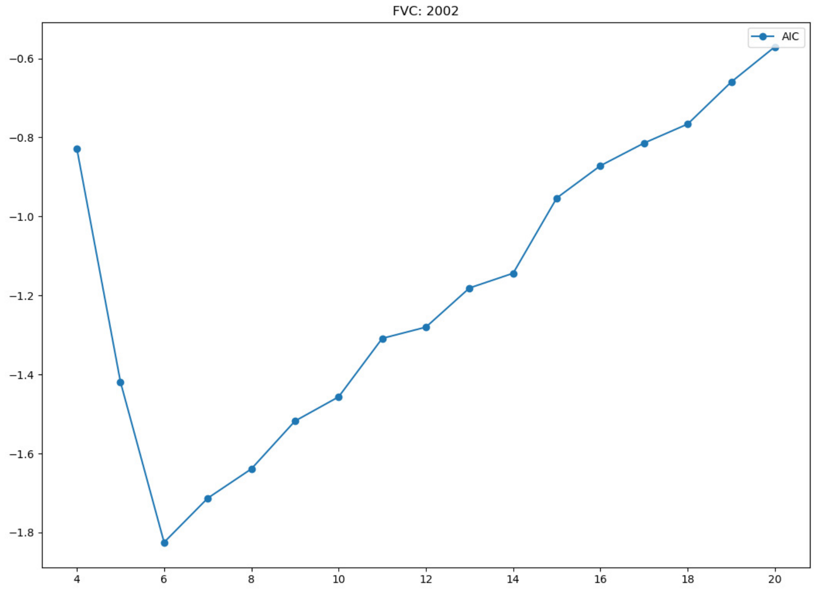

Figure 6. Dependence of the AIC (vertically) on the number of neurons (horizontally).

Table 1. The results of the proposed approach.

	FVC 2002 (DB1)	FVC 2002 (DB2)	FVC 2002 (DB3)	FVC 2002 (DB4)	FVC 2002
FAR	2.099%	2.076%	3.303%	2.435	2.478%
FRR	0.975%	1.613%	1.240%	0.787	1.153%

Of the works known to us, only in [6] are numerical results of segmentation on public fingerprint d atabases w ith a n e stimate o f a ccuracy a t t he p ixel l evel. T he a uthors o f this work claim an average (total) error of 6.8%. They calculate this error based on 30 selected and manually segmented images.

The results of our algorithm are given in Table 1. It is especially worth noting that these results were obtained by pixel-by-pixel comparison of algorithm segmentation with the reference (manually segmented image of the fingerprint). A n i llustration o f t he a lgorithm i s s hown in figure 6.

5. Acknowledgments

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Figure 6. Segmentation with the proposed approach. To the left is a segmentation sample by NET only; to the right by NET+RL+MP. Additional processing allows to eliminate breaks and a spuriously segmented island.

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