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Review Paper on an Authentication System using Siamese Convolutional Neural Networks

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Abstract: *Due to its distinct advantages, finger vein verification has lately drawn more attention. Focusing on the characteristics of finger vein verification, construct a Siamese structure combining with a modified contrastive loss function for training the above CNN, which effectively improves the network's performance. The experimental findings demonstrate that the lightweight CNN's size shrinks to 1/6th of the pretrained-weights based CNN and that it achieves an equal error rate of 75% in the SDUMLA-HMT dataset, which outperforms cutting-edge techniques and nearly maintains the same performance as CNN that is based on pretrained weights.*

Keywords: Finger Vein Verification, Convolutional Neural Network, Siamese CNN

I. INTRODUCTION

Image acquisition, image pre-processing, feature extraction, and matching are the four main components of a finger vein verification system, with feature extraction serving as the most crucial stage. The system's total performance can be markedly enhanced with discriminative image features. Three groups can be made based on the various feature extraction techniques: finger vein pattern-based techniques, finger vein texture-based techniques, and minutiae-based techniques.

In order to solve the image matching issue of signature verification, Siamese nets were first developed by Bromley and LeCun in the early 1990s. (Bromley et al., 1993). Twin networks that take different inputs but are connected by an energy function at the top make up a Siamese neural network. The highest-level feature representation on each side is compared using some measure by this function. There is a connection between the twin networks' characteristics. The same metric as if the opposite twins had been shown the same two pictures.

Weight tying ensures that because each network computes the same function, two extremely similar images cannot possibly be mapped by their separate networks to extremely different locations in feature space. Additionally, because of the network's symmetry, whenever we show two different images to the twin networks, the top conjoining layer computes the same metric as if we had presented the same two images to the opposite twins.

II. LITERATURE SURVEY

Pattern-based methods: This kind of method mainly relies on the information provided by the global structure of the blood vessels. Miura et al. [1] utilized repeated line tracking with randomly varied start points to extract the finger vein patterns. Later, Liu et al. [2] modified the traditional line tracking algorithm to enhance its robustness and reduce the computational cost and noise. In addition, Miura et al. [3] proposed a new method, which extracts the Centre-lines of veins by finding local maximum curvatures in cross-sectional profiles of finger vein images with various widths and brightness levels. Song et al. [4] also investigated the geometrical properties and extracted finger vein patterns using their mean curvature. Moreover, Yang et al. [5] proposed a method to exploit vein information based on gabor filters.

Texture-based methods: The texture of a finger vein image is represented by a grey-scale distribution of pixels. Lee et al. [6] used the local binary pattern (LBP) [7] and local derivative pattern (LDP) [8] to extract finger vein features. Later, Rosdi et al. [9] proposed a new texture descriptor called the local line binary pattern, which shows better results than the LBP and LDP. To further improve the performance, Yang et al. proposed the personalized best bit map [10], and personalized weight maps [11] which assign different weight values for different bits according to their stability. Minutiae-based methods: The minutiae point in finger vein verification refers to bifurcation points and endpoints. Yu et al. [12] extracted the minutiae features from vein patterns and used a modified Hausdorff distance algorithm for matching. Liu et al. [13] proposed minutiae matching method basedon singular value decomposition. The scale- invariant feature transform (SIFT) features were exploited in [14, 15], which show more tolerance to the rotation. In addition to the three main approaches described above, some other methods have been investigated in recent years such as principal component analysis-based methods [16], manifold learning [17] and superpixel-based methods [18]. In summary, the existing finger vein verification algorithms mainly utilize thehandcrafted features, which are sensitive to image quality and finger position. To overcome this issue, various image preprocessing procedures and new features are also investigated, whose measures tend to be complex but the improvements are limited.

Different from general images (such as that of a face), a finger vein image has its owncharacteristics. For example, they are usually grey- scale images, and the information on texture features is relatively scarce and changes slowly and a transition from texture to the background is not sufficiently obvious. Extracting more effective and discriminative features from this type of image is especially vital to make the performances of finger vein verification systems more accurate and robust.In view of the shortcomings within existing traditional finger vein verification algorithms based on handcrafted features and the CNN-based finger vein verification methods, we propose a novel method based on the Siamese CNN to better meet the requirements of finger vein verification. Its contributions are summarized as follows: (i) through the use of image augmentation along with the method of building a CNN based on pretrained weights, we alleviated the issues of lacking trainingsamples for deep learning. (ii) On the basis of the pretrained-weights based CNN, the Siamese structure was constructed for metric learning, and we proposed a new modified contrastive loss (MC loss) function for training, which further improved its discriminative power for features. (iii) Considering a deployment in embedded devices with limited hardware resources, we first developed and trained a pretrained weights-based CNN, whose knowledge was then transferred to a newly built lightweight CNN by a knowledge distillation method, which made the final finger vein verification CNN model small but effective. (iv) We performed a sufficient number of open-set experiments on three public datasets and one self- built dataset, which all verified that our method achieved a state-of-the-art performance.

III. PROBLEM STATEMENT OF SYSTEM

Traditional authentication methods like passwords and magnetic cards are far from meeting the requirements of society given the growing demand for accurate and reliable identity authentication in modern society. This is because they can be easily stolen and falsified. Meanwhile, biometric identifiers (such as fingerprints, faces and iris patterns) are characterized by their uniqueness and stability, making biometric recognition technology more important in the identity authentication field. The finger veins are located beneath the skin, which makes them more difficult to steal or wear than the majority of biometric identifiers that are on the exterior of the body. Most importantly, finger vein verification has the special ability to identify live bodies, which guarantees the benefits of finger vein technology and draws more interest to this field.

IV. IMPLEMENTATION DETAILS OF MODULE

The proposed system contains following:

4.1 Pre-processing

Data will be loaded into the system, checked for accuracy, and then trimmed and cleaned for analysis. Make sure to thoroughly document the cleaning decisions and provide justification. The data that was gathered might have missing numbers, which could cause it to be inconsistent. To gain better results data need to be pre-processed so as to improve the efficiency of the algorithm. Variable conversion must be done after the anomalies have been removed.

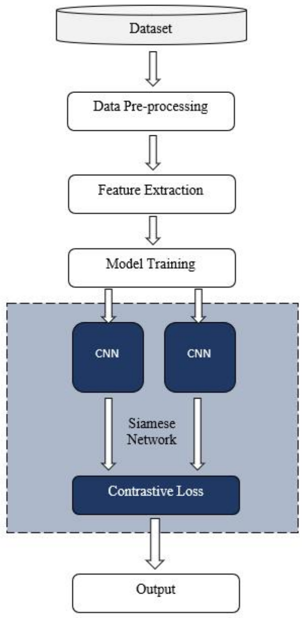

Fig. Model Architecture

4.2 Building the Siamese CNN Model

The Siamese network with a contrastive loss function, which is fed sample pairs and extracts their features to learn the similarity measure of the sample pairs, can meet the requirements for featuresin finger vein verification. Furthermore, the Siamese network can use the learned similarity measure to compare and match samples of new unknown categories, thus it is truly suitable for applying it to a task with a large number of categories, where the number of samples for each category is very small after grouping the samples into pairs.

4.3 Working

Using Siamese neural networks, we learn image representations using a supervised metric-based approach, then reuse their features for one-shot learning without retraining.

In spite of the fact that the basic approach can be applied to almost any modality, we focus on character recognition. To tackle this problem, we use large Siamese convolutional neural networks, which are capable of:

1. Learn generic image features that can be used to predict unknown class distributions even when few examples are available;
2. Could be easily trained on pairs of data samples using standard optimization techniques; and
3. Provide a competitive approach that does not rely on domain-specific knowledge by instead utilizing the strengths of large Siamese convolutional neural networks.

V. CONCLUSION

One advantage of the suggested training structure is that lightweight CNN performs almost as well as the pretrained-weights based CNN while using considerably fewer resources. The size of the dataset required for authentication process will significantly reduce. In order to achieve an even better identification rate, we intend to enhance the imaging gadget and algorithm.

Additionally, we can attempt to create brand-new deep learning modules targeted at particular finger vascular deformations

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