On the use of convolutional neural networks for robust classification of multiple fingerprint captures

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1 Fingerprint classification strategies with deep learning

Fingerprint classification aims to accelerate identification in large databases by grouping the fingerprints into several classes, so that each input is compared only to the templates belonging to its predicted class [4]. It is composed of two steps: feature extraction, and classification. This enables the use of highly accurate classifiers; however, the manually designed feature extraction focuses on specific aspects of the fingerprint pattern, which can lead to some information loss. Some algorithms reject low-quality impressions, which strengthens the classification reliability but hinders the database penetration rate reduction.

Convolutional neural networks (CNNs) [3] extract information from raw patterns such as images, without any manually designed feature extraction. The output of the networks is defined for any input pattern, allowing to eliminate the rejection rate. In this paper, we propose to use CNNs for fingerprint classification with the following aims:

- To **evaluate the accuracy of CNNs** against that of state-of-the-art classifiers based on feature extraction.
- To **increase the robustness** on multiple impressions of the fingerprints.
- To **minimize the penetration rate** along with the identification time.

Synthetic databases of 3 different qualities generated by SFinGe and the public NIST-SD4 were used in a comparative study against the best-performing feature extractors in [1], combined with several well-known classifiers: SVM, C4.5 and k-NN. We considered two CNNs:

- **CaffeNet**: variant of AlexNet [2], fit to the scale of fingerprint classification.
- **Proposal**: a CNN with a smaller number of units than CaffeNet, thus simplifying the search space of the training and to accelerate its convergence.

2 Analysis of the classification accuracy

The experimental study carried out in [1] was replicated; a single impression of each fingerprint was used, making a total of 5 databases: three SFinGe databases with 10 000 images and two NIST-SD4 databases with 1650 images each.

The proposal yielded an accuracy far above any of those obtained by the classifiers with feature extraction (e.g. 0.9754 for low-quality SFinGe). It also outperformed CaffeNet, despite its smaller number of layers and neurons, showing that the smaller search space allows for a better convergence of the learning process. The proposed network was only outperformed by feature extractors and ensembles of them with a very high rejection rate. Nevertheless, in practice it is usually preferable to eliminate such a high rejection rate at the cost of a slight reduction of the accuracy.

3 Analysis of the classification robustness

We used the 3 SFinGe databases (4 impressions of 10 000 fingerprints each), and the NIST-SD4 database (2 impressions of 1650 fingerprints). The first impression was used as training set, while the remaining impressions were stripped of their labels and conformed the test set. After the training, each fingerprint was relabeled with the class assigned by the classifier to the template impression.

The CNNs outperformed all state-of-the-art classifiers (e.g. 0.9640 for low-quality SFinGe), without any rejection. Furthermore, the penetration rate ($\sim$30% for all databases) was lower than for of the compared combinations of feature extractors and classifiers, and very close to the theoretical minimum that can be reached with a 5-class scheme. The proposal performed better than CaffeNet due to its smaller size and the subsequent better generalization capability.

Acknowledgements

This work was partially supported by the Spanish Ministry of Science and Technology under the project TIN2014-57251-P, and the Foundation BBVA project 75/2016 BigDaPTOOLS. Y. Saeys is an ISAC Marylou Ingram Scholar.

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