Impact of variations in synthetic training data on fingerprint classification

Pelin İrtem
Computer Engineering Department
IZTECH
Izmir, Turkey
pelinsenkula@iyte.edu.tr

Emre İrtem
Computer Engineering Department
IZTECH
Izmir, Turkey
emreirtem@iyte.edu.tr

Nesli Erdoğmuş
Computer Engineering Department
IZTECH
Izmir, Turkey
neslierdogmus@iyte.edu.tr

***Abstract*—Creating and labeling data can be extremely time consuming and labor intensive. For this reason, lack of sufficiently large datasets for training deep structures is often noted as a major obstacle and instead, synthetic data generation is proposed. With their high acquisition and labeling complexity, this also applies to fingerprints. In the literature, a number of synthetic fingerprint generation systems have been proposed, but mostly for algorithm evaluation purposes. In this paper, we aim to analyze the use of synthetic fingerprint data with different levels of degradation for training deep neural networks. Fingerprint classification problem is selected as a case-study and the experiments are conducted on a public domain database, NIST SD4. A positive correlation between the synthetic data variation and the classification rate is observed while achieving state-of-the-art results.**

***Index Terms*—fingerprint classification, synthetic ground truth, deep learning**

I. Introduction

Deep neural networks are proven capable of constructing accurate input-to-output mappings for different types of research problems, as long as an appropriate learning formulation and a large specialized data corpus are provided for training. Unfortunately, sufficiently large datasets are unavailable for many domains, including fingerprint analyses.

Collection and labeling of fingerprints is a demanding task in terms of both time and labor. Manual labeling also requires a certain level expertise. Moreover, fingerprint data collection brings about severe privacy and security issues. For these reasons, even before the rise of data hungry machine learning methods, several synthetic fingerprint generation systems were developed [1], [5]. Their purpose was to generate datasets for testing fingerprint matching algorithms against larger galleries, to simulate real-world queries.

In this study, we aim to analyze the use of synthetic fingerprint data with different levels of variation for training deep neural networks. The focus of the research is more about the impact of data variation rather than size. For the experiments, fingerprint classification is selected as a case study, since this task is more in line with traditional image classification problems. To the best of our knowledge, a study of this type has not been published before.

This work is supported by TÜBİTAK.

II. Related Work

The related work can be discussed in three directions: utilization of synthetic data for training deep neural networks, synthetic fingerprint generation methods and deep learning in fingerprint studies, particularly in fingerprint classification.

A. Synthetic data and deep learning

Today, we can safely argue that in the field of machine learning every resource we can think of, from algorithms and their open-source implementations to programming frameworks, from tutorials to online courses is abundant except high quality data. As a result, research focus is drifted towards finding methods to artificially augment real datasets of moderate sizes [20], [25] and to generate training data synthetically [2], [15], [23].

In [23], a synthetic training dataset is utilized for object detection. In order to handle the variability in real-world data, images are generated by randomizing the graphic simulator parameters, without imposing a requirement to be photo-realistic. Nevertheless, competitive results are achieved. In [15], a similar study is done for learning disparity and optical flow estimation, concluding that diversity in the synthesized data is important but realistic effects, such as sophisticated lighting models, are overrated.

B. Synthetic fingerprint generation

Research on synthetic fingerprint generation have started long before the deep learning era. One of the most popular among those studies is [5]. It has also been used in FVC competitions [11] and proven to be beneficial for technology evaluations. In a more recent study [1], another synthetic fingerprint generator, inspired by Sfinge and called Anguli, was proposed. In contrast to SFinGe, Anguli is a freely available tool and mainly for this reason, it is utilized to generate the synthetic fingerprint images in this work. In 2018 Looking at People ECCV Satellite Challenge, it has also been used to generate ground-truth fingerprint images for Track 3 competition [10]. Most recently, in [4], Cao and Jain propose a Generative Adversarial Network to generate rolled fingerprint images. Similar to SFinGe and Anguli, the main motivation is specified as to simulate large scale fingerprint search evaluation.

C. Deep learning in fingerprint research

Just like any machine vision sub-domain, fingerprint analysis also took its share from the influx of deep learning methods. Deep neural networks are adopted both in an end-to-end fashion for fingerprint matching [3], [8] and separately for different stages of fingerprint matching, such as segmentation [17], orientation field estimation [21], minutiae extraction [7], [13], [18], [19], [22]. In those studies, fingerprint researchers try to handle issue of data scarcity in various ways, like implementing patch-based methods [8], [13], [19], and data augmentation [17], [21].

Deep learning architectures are also employed for fingerprint classification. In [24], stacked sparse autoencoders are used for classification with orientation fields as features. By adopting fuzzy classification at the autoencoder output, they claim to increase the classification accuracy from 91.4% to 98.0% on the NIST Special Database 4 (NIST SD4) [26]. However, with the fuzzy method, weakly classified fingerprints are also assigned the second highest probability label, converting the problem into a rank-2 classification.

In [9], Conic Radon Transform is applied on the fingerprint image and the obtained image, combined with its original, is fed into a Convolutional Neural Network (CNN) of 9 layers. An accuracy rate of 96.5% is reported on NIST SD4. Finally in [16], two CNN's (VGG-F and VGG-S) pretrained on ImageNet [6] and fine tuned with NIST SD4 are used to directly classify fingerprint images, without any preprocessing. The accuracy rates of VGG-F and VGG-S networks are found to be 94.4% and 95.05%, respectively.

III. Methodology

In order to analyze how the variability in the synthetically generated training data affect the fingerprint classification performance, synthetic data generated using Anguli [1] software is subjected to different types of variations, resulting in 7 different training sets. Separately or together with real data, these sets are used to train a deep neural network and classification accuracies are calculated on NIST SD4.

A. Synthetic data generation

Firstly, an orientation and a density map are generated and a noise-free master fingerprint is obtained using Anguli [1]. Next, in order to create synthetic training datasets of different characteristics, variations listed and detailed below added externally:

1) Fingerprint area: Fingerprint images can have different shapes due to the varying finger size and contact pressure amount. In order to create randomized masks to crop the master fingerprint, a model controlled by 5 parameters and proposed in [14] is employed (Figure 1).
2) Scale, rotation and translation: Images are rotated by the image center, translated and scaled by random values uniformly sampled from range of (-10.5,+10.5) degrees, (-20,+20) pixels in both x and y directions and (0.5, 1.32) scaling factors, respectively.

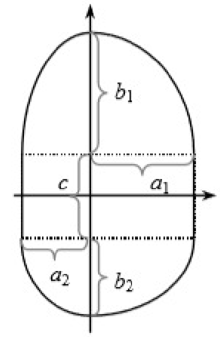

Fig. 1. The fingerprint shape model [14]

3) Background: Background images are generated in multiple stages: Firstly, different paper-like base textures are generated[1]. Next, marks and annotations that often exist on fingerprint images (such as digits, class labels and finger info) are simulated and printed on the background at a random location and scale. Then, lines and dots of random number, position and angle/size and finally, uniform noise are added to the background image and it is blurred by applying a Gaussian filter.
4) Perturbations: Noise that is more prominent at the edges and light at the center is added in blobs of varying size.
5) Deformations: Piecewise affine transformation is applied on a regular grid, to simulate shape deformations at the fingertip that occur when pressed against the acquisition surface.
6) Ridge thickness variation: If the finger tip is dry, friction ridges appear thinner, and otherwise, thicker. In order to simulate this, morphological operators are applied [14].
7) Scars: In order to simulate skin folds and scars, ellipses of random length, thickness, angle and number are added.

In total 7 training datasets are created with following variations: v0: Raw Anguli master fingerprint, v1: 1+2, v2: 1+2+3, v3: 1+2+4+5, v4: 1+2+3+4+5, v5: 1+2+3+4+5+6 and v6: 1+2+3+4+5+6+7. An example for each training dataset and fingerprint class is given in Figure 2.

B. Classification

For fingerprint classification, CNNs with residual network (ResNet-18) topology [12] are used. ResNet's are proven powerful for many applications, mainly because they make it possible to train very deep structures using identity shortcut connections that allow for gradients to flow through. The last layer of the network is configured for fingerprint classification. Cross entropy is used as the loss function and stochastic gradient descent as the optimizer. Instead of random initialization, models are pre-trained on ImageNet [6].

[1] https://stackoverflow.com/questions/51646185/how-to-generate-a-paper-like-background-with-opencv

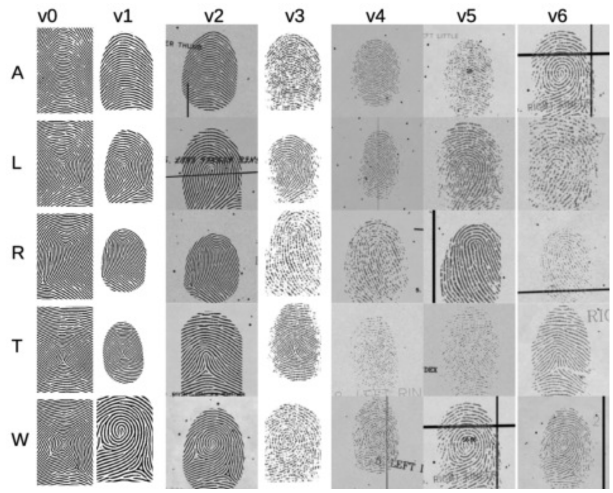

Fig. 2. Synthetic fingerprints of different classes from the the created datasets

IV. Experiments and Results

In parallel to the related existing studies, experiments are conducted with the NIST SD4 benchmark database [26]. NIST SD4 is provided by the National Institute of Standards and Technology in USA and contains 4000 8-bit grayscale fingerprint images of size 512x512. The fingerprint images are manually labeled with one of the five classes: arch (A), left loop (L), right loop (R), tented arch (T) and whorl (W). Each class has two fingerprint images of 400 different fingers. In the dataset, 700 images are labeled with more than one class and those are excluded from the experiments.

As explained previously, 7 synthetic training datasets, each of size 2000, are generated. Using those, two types of experiments are conducted: 1) A classifier is trained using NIST SD4 and tested on the synthetic training datasets to observe the generalization performances. These results are expected to give an idea about the level of similarity between real and synthetic fingerprint images. 2) Classifiers are trained with purely real, purely synthetic and both real and synthetic training data and tested on NIST SD4 to examine the performances. All experiments are conducted in 5-folds.

A. Synthetic data analysis

In order to estimate the "credibility" of the generated synthetic images, they are classified using a ResNet-18 trained on NIST SD4. The results, given in Table I will be discussed together with fingerprint classification results on NIST SD4 in the next subsection.

B. Fingerprint classification

Different combinations of 7 synthetic training sets and NIST SD4 results in 15 different setups. ResNet's are trained with these setups and tested on NIST SD4 (Figure 3).

Distinguishing between arch and tented arch classes can be difficult even for human experts. For this reason, in the literature, these classes are often merged, resulting in 4-category classification problem instead of 5. In this study, our classifiers are trained and tested with 5 classes but for comparison, 4-class success rates are also evaluated by accepting arch estimations correct for tented arch fingerprints and vice versa.

The results clearly show that using purely synthetic data is not sufficient and the highest success rates, 80.82% and 79.91% achieved by v4 and v5 are still much lower than the result achieved training without any synthetic data (95.61%). On the other hand, a clear correlation can not be observed between the "credibility" scores and the contribution of the synthetic datasets. This is mainly because the added variations also change the classification difficulty of the fingerprint images. The synthetic datasets with clear ridge lines are found to have higher classification rates (v0 and v2).

When used for training with real data, synthetic data could introduce minor improvements for almost all sets, v6 being the highest contributor with a success rate of 95.76%. This rate goes up to 96.97% for 4-category classification and it surpasses the state-of-the-art results, such as [16]. Being the training set with maximum number of variations, it is not surprising that v6 emerged the victor. However, an error-analysis is needed in more depth to be able to generate more rewarding datasets.

V. Conclusion

In this study, a methodology to generate synthetic fingerprint images with different variations is presented. Differently than existing studies that involve synthetic fingerprint images, their contribution to fingerprint classification using deep learning is analyzed. For this purpose, ResNet-18 topology is adopted and trained with many different experimental setups. The results have shown that increasing the variability in the synthetic data is beneficial but its assistance can be improved.

In the future, we would like to inspect and optimize the parameters to add variations on the synthetic fingerprint images to further increase the classification rates. Additionally, we aim to conduct similar experiments for other stages of fingerprint matching, that have been carried out using deep neural networks.

Acknowledgment

This work is supported by 2515 - COST (European Cooperation in Science and Techology) program of TUBITAK, with the project numbered 217E092.

References

[1] Ansari, Afzalul Haque: Generation and storage of large synthetic fingerprint database. ME Thesis, Jul, 2011.
[2] Barbosa, Igor Barros; Cristani, Marco; Caputo, Barbara; Rognhaugen, Aleksander; Theoharis, Theoharis: Looking beyond appearances: Synthetic training data for deep cnns in re-identification. Computer Vision and Image Understanding, 167:50–62, 2018.
[3] Cao, Kai; Nguyen, Dinh-Luan; Tymoszek, Cori; Jain, Anil K: End-to-End Latent Fingerprint Search. arXiv preprint arXiv:1812.10213, 2018.
[4] Cao, Kai; Jain, Anil: Fingerprint synthesis: Evaluating fingerprint search at scale. In: International Conference on Biometrics (ICB). IEEE, pp. 31–38, 2018.
[5] Cappelli, Raffaele; Maio, D; Maltoni, D: SFinGe: an approach to synthetic fingerprint generation. In: International Workshop on Biometric Technologies. pp. 147–154, 2004.
[6] Deng, Jia; Dong, Wei; Socher, Richard; Li, Li-Jia; Li, Kai; Fei-Fei, Li: Imagenet: A large-scale hierarchical image database. In: Conference on computer vision and pattern recognition. IEEE, pp. 248–255, 2009.

TABLE I
5-CLASS CLASSIFICATION ACCURACIES FOR THE SYNTHETIC DATASETS AND NIST SD4 WHEN THE LATTER IS USED FOR TRAINING.

	v0	v1	v2	v3	v4	v5	v6	NIST SD4
mean	79.34%	66.96%	95.88%	47.59%	84.60%	77.33%	76.74%	95.61%
variance	12.39%	09.91%	03.12%	11.36%	05.24%	06.19%	05.96%	01.37%

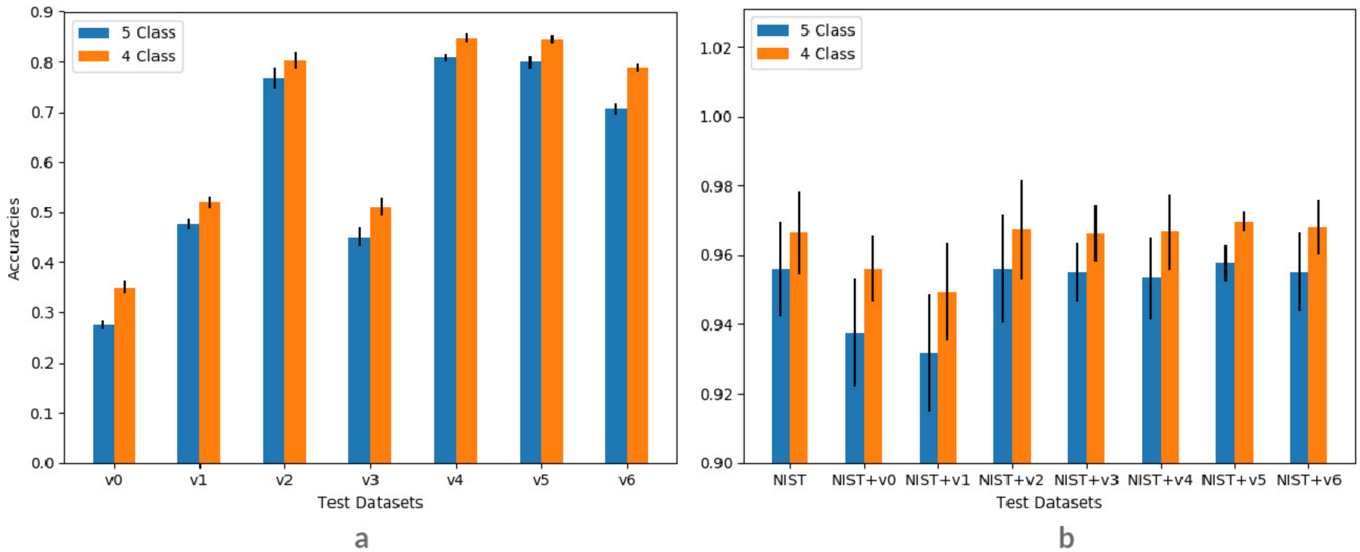

Fig. 3. Classification results for different training setups

[7] Darlow, Luke Nicholas; Rosman, Benjamin: Fingerprint minutiae extraction using deep learning. In: International Joint Conference on Biometrics. IEEE, pp. 22–30, 2017.

[8] Ezeobiejesi, Jude; Bhanu, Bir: Patch Based Latent Fingerprint Matching Using Deep Learning. In: 2018 25th IEEE International Conference on Image Processing (ICIP). IEEE, pp. 2017–2021, 2018.

[9] El Hamdi, Dhekra; Elouedi, Ines; Fathallah, Abir; Nguyuen, Mai K; Hamouda, Atef: Combining Fingerprints and their Radon Transform as Input to Deep Learning for a Fingerprint Classification Task. In: 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV). IEEE, pp. 1448–1453, 2018.

[10] Fingerprint inpainting and denoising (WCCI'18, ECCV'18), http://chalearnlap.cvc.uab.es/dataset/32/description/, Stand: 15.06.2019.

[11] FVC2004 - Third International Fingerprint Verification Competition, http://bias.csr.unibo.it/fvc2004/, Stand: 15.06.2019.

[12] He, Kaiming; Zhang, Xiangyu; Ren, Shaoqing; Sun, Jian: Deep residual learning for image recognition. In: IEEE conference on computer vision and pattern recognition. pp. 770–778, 2016.

[13] Jiang, Lu; Zhao, Tong; Bai, Chaochao; Yong, A; Wu, Min: A direct fingerprint minutiae extraction approach based on convolutional neural networks. In: 2016 International Joint Conference on Neural Networks (IJCNN). IEEE, pp. 571–578, 2016.

[14] Maltoni, Davide; Maio, Dario; Jain, Anil K; Prabhakar, Salil: Synthetic fingerprint generation. Handbook of fingerprint recognition, pp. 271–302, 2009.

[15] Mayer, Nikolaus; Ilg, Eddy; Fischer, Philipp; Hazirbas, Caner; Cremers, Daniel; Dosovitskiy, Alexey; Brox, Thomas: What makes good synthetic training data for learning disparity and optical flow estimation? International Journal of Computer Vision, 126(9):942–960, 2018.

[16] Michelsanti, Daniel; Guichi, Yanis; Ene, Andreea-Daniela; Stef, Rares; Nasrollahi, Kamal; Moeslund, Thomas B: Fast fingerprint classification with deep neural network. In: International Conference on Computer Vision Theory and ApplicationsInternational Conference on Computer Vision Theory and Applications. SCITEPRESS Digital Library, pp. 202–209, 2018.

[17] Nguyen, Dinh-Luan; Cao, Kai; Jain, Anil K: Automatic latent fingerprint segmentation. In: IEEE International Conference on BTAS. 2018.

[18] Nguyen, Dinh-Luan; Cao, Kai; Jain, Anil K: Robust minutiae extractor: Integrating deep networks and fingerprint domain knowledge. In: International Conference on Biometrics (ICB). IEEE, pp. 9–16, 2018.

[19] Sankaran, Anush; Pandey, Prateekshit; Vatsa, Mayank; Singh, Richa: On latent fingerprint minutiae extraction using stacked denoising sparse autoencoders. In: International Joint Conference on Biometrics. IEEE, pp. 1–7, 2014.

[20] Salamon, Justin; Bello, Juan Pablo: Deep convolutional neural networks and data augmentation for environmental sound classification. Signal Processing Letters, 24(3):279–283, 2017.

[21] Schuch, Patrick; Schulz, Simon-Daniel; Busch, Christoph: Deep expectation for estimation of fingerprint orientation fields. In: International Joint Conference on Biometrics (IJCB). IEEE, pp. 185–190, 2017.

[22] Tang, Yao; Gao, Fei; Feng, Jufu; Liu, Yuhang: Fingernet: An unified deep network for fingerprint minutiae extraction. In: International Joint Conference on Biometrics (IJCB). IEEE, pp. 108–116, 2017.

[23] Tremblay, Jonathan; Prakash, Aayush; Acuna, David; Brophy, Mark; Jampani, Varun; Anil, Cem; To, Thang; Cameracci, Eric; Boochoon, Shaad; Birchfield, Stan: Training deep networks with synthetic data: Bridging the reality gap by domain randomization. In: IEEE Conference on Computer Vision and Pattern Recognition Workshops. pp. 969–977, 2018.

[24] Wang, Ruxin; Han, Congying; Guo, Tiande: A novel fingerprint classification method based on deep learning. In: 2016 23rd International Conference on Pattern Recognition (ICPR). IEEE, pp. 931–936, 2016.

[25] Wang, Jason; Perez, Luis: The effectiveness of data augmentation in image classification using deep learning. Convolutional Neural Networks Vis. Recognit, 2017.

[26] Watson, Craig I; Wilson, CL: NIST Special Database 4. Fingerprint Database, National Institute of Standards and Technology, 17(77), 1992.