Generative Adversarial Network (GAN) based Data Augmentation for Palmprint Recognition

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***Abstract*— Palmprint recognition is a very important field of biometrics, and has been intensively researched on both feature extraction and classification methods. Recently, deep learning techniques such as convolutional neural networks have demonstrated clear advantages over traditional learning algorithms for various image classification tasks such as object recognition and detection. However, a large amount of data is needed to train deep networks, which limits its application to some tasks such as palmprint recognition where it lacks of sufficient training samples for each class (i.e., each individual). In this paper, we propose a Generative Adversarial Net (GAN) based solution to augment training data for improved performance of palmprint recognition. An improved Deep Convolutional Generative Adversarial Net (DCGAN) is first devised to generate high quality plamprint images by replacing convolutional transpose layer with linear upsampling and introducing Structure Similarity (SSIM) index into loss function. As a result, the generated images have discriminative features, increased smoothness and consistency, and less variance compared to those generated by the baseline DCGAN. Then, a mixing training strategy via a combination of GAN-based and classical data augmentation techniques is adopted to further improve recognition performance. The experimental results on two publicly available datasets demonstrate the effectiveness of our proposed GAN based data augmentation method in palmprint recognition. Our method is able to achieve 1.52% and 0.37% Equal Error Rates (EER) on IIT Delhi and CASIA palmprint datasets, respectively, which outperforms other existing methods.**

***Index Terms*—Generative Adversarial Network (GAN), Palmprint recognition, Biometrics, Data augmentation**

I. Introduction

Palmprint recognition is a very important field of biometrics. It has a wide range of promising applications in the area of security and surveillance due to its unique nature of data acquisition. For example, it is challenging to produce forgery palmprints due to the difficulty of collecting information of an entire palm. Comprehensive research has been conducted on palmprint recognition for decades, such as offline recognition with inked palmprints [1] and online recognition with digital palmprint images [2] [3] [4] [5].

As a classical pattern recognition task, palmprint recognition generally involves two steps: feature extraction and feature classification. The first step aims to devise novel features for discriminative representation of each plamprint image, and the second step relies on classifiers or classification models. The discriminative features are generally hand-crafted based on the domain insights from researchers.

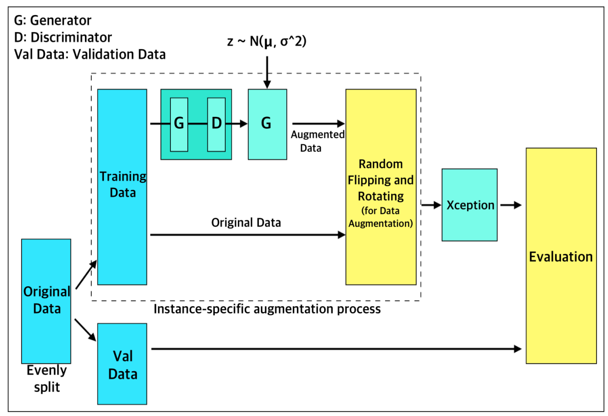

Fig. 1: Illustration of our proposed palmprint recognition with GAN based data augmentation.

Recently, deep learning based techniques [6] have demonstrated great promises for many computer vision tasks such as object recognition and detection with Convolutional Neural Networks (CNN), proposed by LeCun et al. [7]. In general, CNNs can be used as a data-driven feature extractor which perform feature extraction at different levels along as the depth of network increases. Therefore, there have been several attempts (e.g., [8], [9], [3]) of applying deep learning techniques to palmprint recognition. As deep learning methods generally require sufficient training samples to train the large number of network parameters, the learning capacity of deep learning techniques may have not been well exploited due the limited training samples each class (i.e., a person or subject) in the field of biometrics.

Various data augmentation techniques have been explored and introduced. Most of such techniques [10], [6] utilise a set of linear operations including random rotating, shifting, cropping, and adding noise to increase the number of training samples. Although they are effective for addressing the issue of lack of training samples, the improvement is restricted due to the limited number of linear operations and the content of dataset. Recently, Generative Adversarial Network (GAN)

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proposed by Goodfellow et. al, [11] and its variants such as Deep Convolutional GAN (DCGAN) [12] demonstrate great promises in generating images which are highly similar to a given set of training images. This provides a great opportunity for augmenting training samples with great variety to improve the generalisation of deep learning methods.

There have been various studies on GAN based data augmentation [13] [14] [15], however, little research has been conducted in the field of palmprint recognition. In this paper, we propose a GAN based data augmentation method for palmprint recognition. Although DCGAN has been successfully used to generate samples for training data augmentation, it often suffers from a number of issues when being applied to plamprint generation, such as losing critical discriminative features (i.e., palmlines) and large variation between generated samples and input samples, which may not be helpful for training a better deep network. Therefore, we improve the standard DCGAN from two aspects. Firstly, a simplified linear upsampling layer is devised to replace the convolutional transpose layer, which will reduce the number of parameters to be trained without a large number of training samples. Such linear upsampling is also helpful for restricting the variation of generated samples. Secondly, we integrate the Structural Similarity (SSIM) index into the loss function to further ensure that generated samples are similar with training data in terms of overall structure. As a result, with limited training data and simplified network architecture, our improved DCGAN is capable of producing structurally consistent samples compared with training data.

We evaluate our proposed GAN based data augmentation method for palmprint recognition as illustrated in Fig. 1. Experimental results on two widely used datasets demonstrate that our proposed data augmentation method is helpful for improving recognition.

The rest of this paper is organised as followed: Section II presents a brief overview of recent approaches of relevant fields, Section III explains our proposed GAN architecture, Section IV describes our recognition model, Section V presents the experimental results on two widely used palmprint datasets, and Section VI concludes the paper.

II. Related Work

In this section, we review relevant literature from two topics, plamprint recognition and data augmentation.

A. Palmprint Recognition

As a classical pattern recognition problem, traditional palmprint recognition methods mainly focus on extracting representative and discriminative features from palmlines by leveraging domain knowledge. Many handcrafted features have been proposed, including coding features, texture-based features, line direction features, and local descriptor features. For example, Zhang et.al [16] attempted using competitive code [17] and Palmprint Orientation Code (POC) [18] to deal with low contrast palmprint images. Recent methods for feature extraction mainly focus on improving existing features. Luo et al. [5] invented local line directional patterns and Fei et al. [19] proposed local multiple directional patterns to characterise directional patterns of palmprints empirically. Sun et.al [20] proposed an optimised formulation to select ordinal features. A more detailed review is available in a recent survey paper.

Recently, deep learning techniques such as CNN have also been utilised for palmprint recognition due to their significant success in many vision tasks such as object detection and recognition. In general, there are two deep learning strategies for palmprint recognition: using a deep network as an advanced feature extractor through representation learning, and training a deep network in an end-to-end way. For example, in [9], principle component analysis is applied to deep features (e.g., the vector before the fully connected layer) for dimension reduction and a support vector machine is trained on the dimension reduced feature vectors for recognition. In [3], a convolutional neural network with improved loss functions was proposed for end-to-end training and recognition. However, advanced data augmentation has not been well explored in these deep learning based methods.

B. Data Augmentation

As small datasets generally do not provide sufficiently representative training samples, which could lead to model overfitting, data augmentation has been necessary for applying deep learning techniques to applications with small training dataset. Effective data augmentation can help reduce intra-class distances and increase inter-class distances.

Conventional data augmentation techniques include but not limited to: horizontally/vertically shifting, random cropping, zoom in/out, rotation, adding random noise etc, which are mostly geometric transformations. On the other hand, using GAN as a generator for data augmentation has been a promising solution. As a generative model, it learns the data distribution of training samples and generates samples similar to input data. Furthermore, GAN based data augmentation is not constrained by the size and the number of categories of training data. It is noteworthy that while traditional GAN models focus on data generation with sufficient diversity, GAN models for data augmentation focus more on consistence instead. As it is difficult to train GANs due to the convergence issue, many improvements have been made for GAN training such as [21], [22] and [23]. There are several attempts such as [14], [15], [13] that successfully use various GAN models for image synthesis and data augmentation in the field different with palmprint recognition. Our work in particular aims to address the consistence issue by introducing SSIM index in the loss function.

III. GAN-Based Data Augmentation

Deep Convolutional GAN (DCGAN) [12], which is the first GAN model utilising convolutional layer and has achieved successful outcomes on producing high quality images, is selected as the basis of our framework. The training strategy is to define two adversarial networks competing against each other, namely generator (G) and discriminator (D), which are generally two neural networks that can be trained with

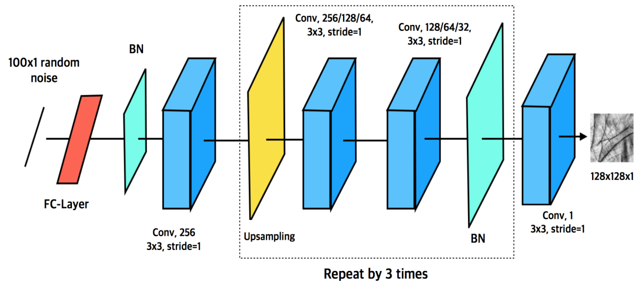


Fig. 2: Illustration of our proposed generator.

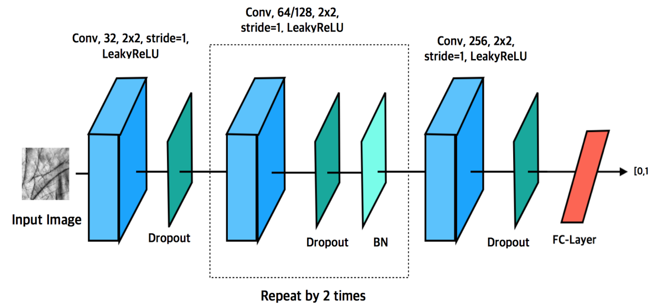


Fig. 3: Illustration of our discriminator.

classical backpropagation algorithm. In the training process, G aims to learn and produce “fake" samples from input noise z to fool D while D attempts to distinguish “fake" from “genuine" inputs correctly. Note that the input noise z generally follows a Gaussian distribution through G to produce sample $I = G(z)$ where $z = N(\mu, \sigma^2)$, and D is a standard neural network classifier for binary classification. To better visualize our proposed architecture, we use different colors to represent different layers or operations in Fig. 2 and Fig. 3: red for fully-connected layer, blue for convolutional layer, yellow for upsampling layer, light green for batch-normalization and dark green for dropout.

A. Generator

Our generator aims to produce 128×128 samples from a 100-dimension random vector. As shown in Fig. 2, the input directly feeds into a fully-connected layer with 65,536 units, then is reshaped into dimensions of $16 \times 16 \times 256$. It then goes through a batch normalisation layer and a convolutional layer with 256 filters and kernel size of 1. The convolutional output goes through three modules with the same structures. Each module starts with an upsampling layer which doubles the sizes of columns and rows of the input simultaneously through simple linear operation, followed by two stacked convolutional layers of which the second layer has a half number of filters of the first one, and a batch normalisation layer. After these three modules, the output is compressed by another convolutional layer with only one filter. The same activation function is utilised as in DCGAN. That is, ReLU [24] is used in all layers, except for the last convolutional layer where tanh is used.

The linear upsampling layers is inspired by [25] and operates identically. Intuitively, it expands horizontally then vertically using original pixels twice, while other factors can be implemented similarly. With input I of size $W \times H$, the output I' is of size $2W \times 2H$:

$$\begin{aligned} I[i][j] &= I'[2i][2j] \\ &= I'[2i+1][2j] \\ &= I'[2i][2j+1] \\ &= I'[2i+1][2j+1]. \end{aligned} \tag{1}$$

While traditional GAN models are expected to samples which are “creatively” different from input data, our GAN model aims to preserve representative visual features without overfitting. Therefore we introduce SSIM [26] index into the loss function for measuring the similarity between generated images and input ones. SSIM index evaluates difference in terms of structural difference, luminance and contrast. Denote the mean, variance and covariance between inputs A, B as μ, σ and σ_{AB}, it is formulated as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c1)(2\sigma_{xy} + c2)}{(\mu_x^2 + \mu_y^2 + c1)(\sigma_x^2 + \sigma_y^2 + c2)}, \tag{2}$$

$$c1 = (k_1 * L)^2, \tag{3}$$

$$c2 = (k_2 * L)^2, \tag{4}$$

where k_1 and k_2 are constants for regularisation purposes to increase the stability, and L is the possible range of data. We set k_1 to 0.01, k_2 to 0.03, and L to 255 as suggested in [12] in our experiments. Denote the training set as R, target value as t and output from discriminator $y = D(G(z))$, the loss function of the generator is updated to:

$$L_G = -t * log(y) - (1-t) * log(1-y) - \alpha * log(S), \tag{5}$$

where α is a hyper-parameter set to 0.5 in our experiments, and S is the average SSIM value of all pairs of generated sample and training sample in the current iteration:

$$S = \frac{\sum SSIM_{z\sim N, r\sim R}(G(z)', r)}{|R|} \in (0,1). \tag{6}$$

It is noteworthy that $G(z)'$ is the scaled result from $G(z) \in (-1,1)$ to $(0,255)$ for SSIM calculation. In addition to introduce a new componnent in the loss function, we have also changed the architecture of both components to better fit the objective of the task, which will be described in later sections.

B. Discriminator

As shown in Fig. 3, our discriminator is a simple CNN model. It consists of four blocks and each block contains a convolutional layer, a batch normalisation layer and a dropout layer. We adapted the idea in [12] and used Leaky ReLU [27] in all convolutional layers. We investigated whether the batch normalisation layer should be placed before or after the activation layer, and observed no significant difference between these two cases.

IV. Palmprint Recognition

We choose Xception model proposed by Chollet [28] as our recognition method due to state-of-the-art performance in terms of computational efficiency and recognition accuracy. It was developed on GoogLeNet Inception V3 by introducing separable convolutional layer which consists of a depthwise convolutional layer followed by another convolutional layer with kernel size 1. It is also integrated with the residual block and has apparently accelerated the convergence speed with high recognition accuracy. In addition, the pre-trained model on ImageNet is easily accessible, which allows us to apply transfer learning conveniently.

Our final method is as follows. We perform DCGAN based augmentation prior to classical techniques. For each class in the training set, we generate twice samples of existing images. In order to take advantage of both traditional data augmentation strategy and our improved DCGAN based data augmentation strategy, mixed augmented samples are used for training. That is, we feed the mix of the samples in the original dataset and DCGAN generated samples into the process of classical data augmentation including 5% $\sim$ 15% horizontally/vertically shifting, 5% $\sim$ 15% zooming in, random cropping and rotation. To sum up, two methods collectively increase the size of the training set by more than 200 times eventually and successfully result in improved performance. Additionally, we fine-tune the parameters with Adam [29] optimiser and noticed that setting learning rate to 1.5×10^{-4} and $\beta 1$ to 0.5 produces the best result. Cross entropy is used as the loss function for both components.

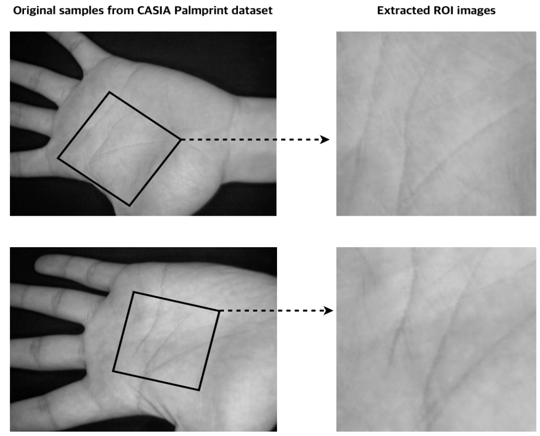


Fig. 4: Samples of our extracted ROI images.

V. Experimental Results and Discussions

A. Datasets

Our experiments are conducted on two widely used touchless palmprint datasets, namely CASIA Palmprint dataset [30] and IIT Delhi Palmprint database [31]. As mentioned before, both datasets were collected by professional researchers using dedicated devices. However, they still have a considerably small number of images per class than the datasets collected for the classification of general objects such as *person* and *car*. The CASIA Palmprint dataset [30] contains 5,464 images from 312 individuals. For each person, both left and right palmprint images are captured. The IIT Delhi Palmprint Database was collected from 235 persons and Region of Interest (ROI) images are provided at resolution 192×192. There are 1,400 images for left hand and 1,391 for right hand. Since there is no quality difference between the images of two hands, we use left hand data only for all further experiments. There are fewer than 7 images per person in the CASIA Palmprint Dataset [31] and fewer than 10 images per person in the IIT Delhi Palmprint Database [30]), which highly likely leads to overfitting during training.

For the CASIA palmprint dataset, we believe using raw data would not result in satisfactory results since the touchless palmprint dataset contains too much noise in backgrounds, and decide to perform ROI extraction to highlight palmprint patterns. The algorithm developed in [32] was used to successfully extract corresponding regions most of the time. We fine-tuned the parameters in the raw ROI extraction algorithm and acquired samples of 294 persons for left hand used in our experiments for comparison, and 289 for right hand. We manually inspected the extracted ROI images and removed the wrongly extracted background regions. The extracted ROI images are at resolution 192×192 and resized to 128×128 for all further usage including both recognition and DCGAN training. Several samples are as shown in Fig. 4. We also attach statistics of our used datasets in Table I. We split the dataset by half roughly for training and testing. If an instance contains n images where n is odd, we take $(n-1)/2$ images to the testing set and the rest to the training set.

By contrast, the ROI images are directly available in the IIT Delhi Palmprint database. We performed no other preprocessing steps except resizing them to 128×128. While we noticed that several samples are not intactly extracted, i.e. having some inconsistent black margin that may potentially compromise the performance, we decide to keep them.

B. Evaluation Metrics

The evaluation metric EER has been commonly used for many tasks in biometrics field, such as palmprint recognition and fingerprint recognition. We also use it to evaluate the effectiveness of our proposed DCGAN based data augmentation method for palmprint recognition. EER indicates how accurate a recognition method is for one-to-one identity verification task. It focuses more on whether a method is capable of distinguishing the difference between various instances.

We calculate intra-class scores and inter-class scores on a trained recognition model. Intra-class scores are the distances between samples of the same person, where inter-class scores are computed from each sample-pair that comes from two different persons. Cosine distance is used in our experiments, and we suggest that introducing an epsilon $1e-9$ is necessary to prevent all-zero vectors from causing calculation errors. The False Acceptance Rate (FAR) and False Rejection Rate (FRR)

TABLE I: Statistics of the original dataset and the dataset we used in our experiments.

	Original			Training				Testing			
Dataset	Total	Left	Right	Total	Average	Min	Max	Total	Average	Min	Max
IIT Delhi	2,791	1,400	1,391	760	3.234	3	6	640	2.723	2	5
CASIA	5,502	2,746	2,756	1,166	4.035	2	9	1090	3.772	2	8

TABLE II: Comparison of recognition performance in terms of EER

Methods	CASIA	IIT Delhi
ULBP [2]	4.35%	NA
Siamese CNN [3]	3.15%	6.08%
Orientation Code [4]	2.98%	NA
Ordinal Code [3]	2.41%	2.08%
D-prime CNN [3]	1.86%	1.64%
Skeleton Filter [33]	0.93%	1.48%
LLDP [5]	NA	4.07%
Fusion Schemes [34]	NA	2.34%
Local Multiple DP [19]	NA	2.64%
Xception + GAN generated images	9.4878%	22.3728%
Xception + Original images	1.2890%	3.0508%
Our Approach	**0.3696%**	**1.515%**

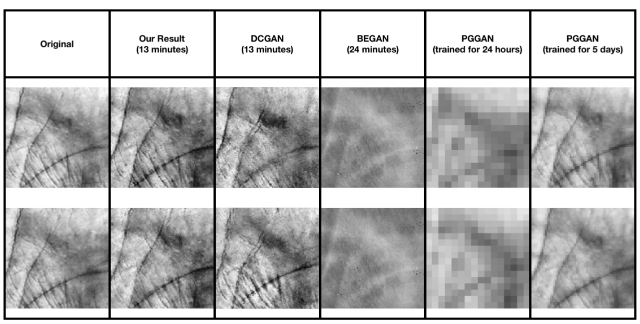
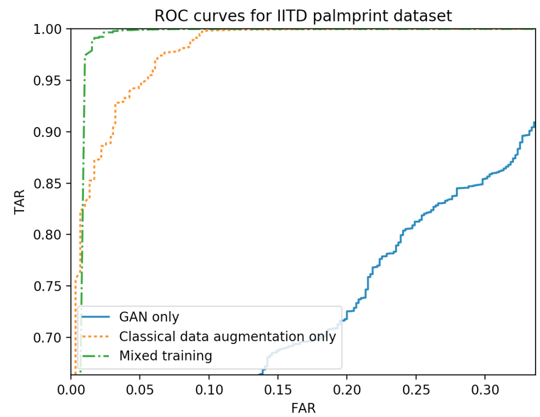
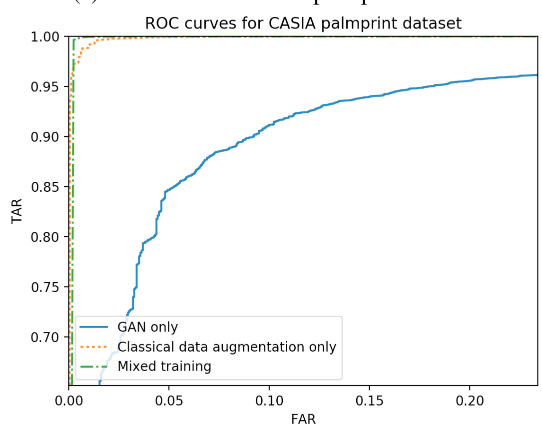


Fig. 5: Comparisons of the samples generated by different GAN models.



(a) ROC curve on IITD palmprint dataset



(b) ROC curve on CASIA palmprint dataset

Fig. 6: ROC curves of the three Xception based palmprint recognition methods on the IITD and CASIA palmprint datasets, respectively. It is observed that combining both the samples obtained through traditional augmentation and DCGAN based augmentation achieves the best performance.

can be calculated via intra-class scores and inter-class scores respectively. In general, FAR increases and FRR decreases as the threshold gets closer to 1, and they intersect at a point which is defined as equal error rate. The lower the EER is, the higher the performance of the recognition method is.

C. Performance Comparison

We compare our proposed data augmentation method with others in terms of its effectiveness on recognition performance and the visual quality of its generated training samples.

1) Recognition Performance: We compared our recognition method with a number of recent palmprint recognition methods including both traditional ones and deep learning based ones such as Siamese CNN as well as D-prime CNN both come from [3]. As shown in Table II, our method achieves the best performance on the CASIA Palmprint dataset. It is also noticed that using DCGAN generated training images does not lead to improved recognition performance, while combining both traditionally augmented samples with DCGAN generated samples is able to achieve the best recognition performance. This demonstrates the benefit of using DCGAN generated sample images. The detailed performance comparison among Xception based methods is listed in Receiver Operating Characteristic (ROC) curves shown in Fig. 6.

On the IIT Delhi Palmprint dataset, our proposed method also achieves performance that is generally on the same level of the best performance [33] included, yet this can be caused by many factors such as random selection of mini-batch and different split of dataset etc. Consequently we consider conducting more experiments simply for a better result is

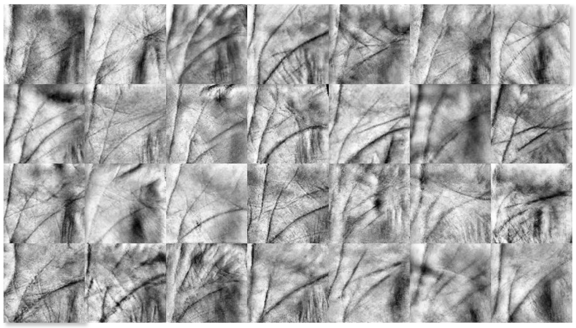


Fig. 7: Samples generated by our proposed DCGAN on the IITD palmprint dataset.

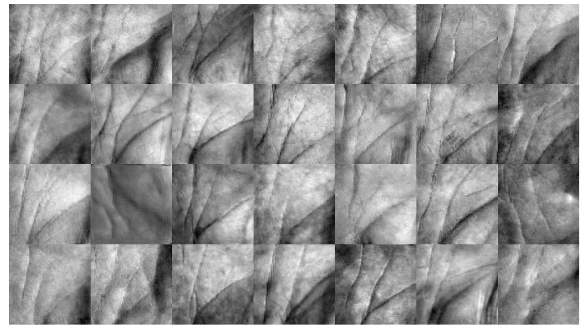


Fig. 8: Samples generated by our proposed DCGAN on the CASIA palmprint dataset.

not valuable and we have already outperformed the same method by a large margin on the first dataset, which can be a strong proof. We noticed that for some specific classes, certain number of noise images (i.e. can hardly be identified similar with the majorities within the same class) exist. This problem becomes more severe when the data is split for evaluation purposes, and when GAN learns distribution from noise images, it inevitably worsen the recognition accuracy.

2) Image Quality: We compare the visual quality of the samples generated by our proposed DCGAN (our result) with those generated by three other GAN models: standard DCGAN [12], Boundary Equilibrium GAN (BEGAN) [23], and Progressive Growing GAN (PGGAN) [35], as DCGAN is the first success GAN model in generation tasks that utilises convolutional layer, BEGAN is able to balance between discriminator and generator to achieve convergence with the same method used in [22], and PGGAN is the latest and the first model that is capable of generating high-resolution face images.

As shown in Fig. 5, the samples generated by our DCGAN are of higher quality than the samples generated by the original DCGAN model. In particular, BEGAN and PGGAN converge much slower than our proposed DCGAN, which is the reason that we did not deploy these model for data augmentation and recognition. Unlike generation tasks which usually emphasis on the image quality and realness, data augmentation also values efficiency and light model (i.e. with reasonable depth and running time) would be more desirable and transferable to other tasks. More generated samples on the two datasets are separately shown in Fig. 7 and Fig. 8.

VI. Conclusion and Future Work

In this paper, we present a novel DCGAN to generate high quality samples for more effective data augmentation in palmprint recognition. In order to reduce the number of network parameters, we replace the convolutional transpose layer with linear upsampling layer. In order to ensure the structure consistence between input samples and generated samples, we introduce SSIM index between input and generated sample in the loss function. Experimental results on two widely used palmprint datasets indicate that our proposed DCGAN is able to produce visually higher quality samples than several state-of-the-art GAN models. Together with an existing deep learning method, our data augmentation strategy is able to deliver the best palmprint recognition methods among all the deep learning based methods. In the future, we will further increase the number of generated samples and investigate how to further improve the recognition performance to eventually outperform one handcrafted feature based method.

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