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Context-aware Restoration of Noisy Fingerprints

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Abstract—Literature on fingerprint restoration algorithms firmly advocates exploiting *contextual information* such as ridge orientation field, ridge spacing, and ridge frequency to recover ridge details in fingerprint regions with poor quality ridge structure. However, most state-of-the-art convolutional neural network based fingerprint restoration models exploit spatial context only through convolution operations. Motivated by this observation, this paper introduces a novel *context-aware* fingerprint restoration model: context-aware GAN (CA-GAN). CA-GAN is explicitly regularized to learn spatial context by ensuring that the model not only performs fingerprint restoration but also accurately predicts the correct spatial arrangement of randomly arranged fingerprint patches. Experimental results establish better fingerprint restoration ability of CA-GAN compared to the state-of-the-art.

Index Terms—Fingerprints, Image Restoration, Biometrics.

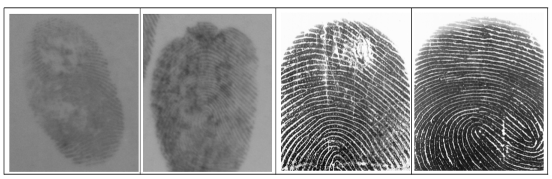

Fig. 1. Sample noisy fingerprints used in this research. The first two fingerprint samples are latent fingerprints taken from [1]. The last two samples are live-scan fingerprints of the rural Indian population taken from the rural Indian fingerprint database [2]. Latent fingerprints possess smudged ridge patterns, while rural Indian fingerprints have missing ridge details due to scars and warts and poor ridge-valley clarity due to dry or wet fingerprints.

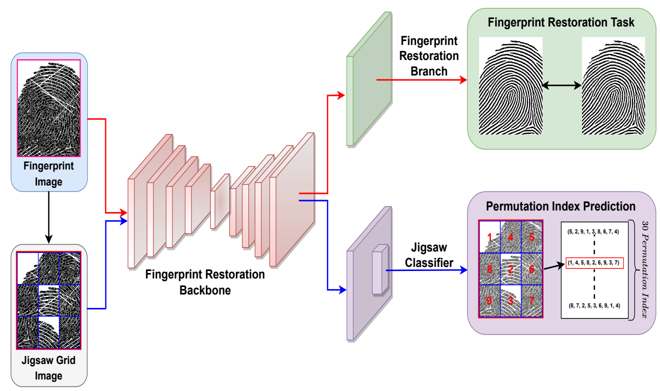

Fig. 2. Schematic diagram of the proposed CA-GAN. To enforce learning of spatial context, CA-GAN exploits multi-task learning. An additional jigsaw classifier is introduced at the last layer. The jigsaw classifier is trained to predict the correct permutation index indicating the relative ordering of fingerprint image patches. As a result, CA-GAN is trained to minimize a weighted combination fingerprint restoration ($\mathcal{L}_{res}$) and jigsaw classification loss ($\mathcal{L}_{jig}$).

I. INTRODUCTION AND RELATED WORK

Fingerprints are among the most accurate and reliable biometric traits, which allows its applications in several domains, including digital transactions, criminal identification, and access control [3]–[7]. However, heavy noise is observed for fingerprints originating from a crime scene, commonly called *latent fingerprints* and fingerprints originating from individuals with poor skin condition around fingertips due to excessive manual work, such as fingerprints of the rural Indian population (see Figure 1). As a result, incorrect ridge features are extracted around noisy fingerprint regions, and the fingerprint recognition performance obtained by an automated fingerprint recognition (AFRS) is significantly degraded for such fingerprints [8]. To address this limitation of AFRS, a fingerprint restoration algorithm is designed to provide better quality fingerprints by predicting missing ridge-valley information and enhancing ridge-valley contrast. Subsequently, improved ridge feature extraction and fingerprint recognition performance is obtained on fingerprints generated using a fingerprint restoration model. Motivated by the contribution of a fingerprint restoration model to improve fingerprint recognition of noisy fingerprints, this paper presents context-aware GAN (CA-GAN), a novel method for fingerprint restoration.

Several classical image processing based methods for fingerprint restoration advocate exploiting *contextual information* such as ridge frequency, ridge spacing, and ridge orientations to recover missing ridge characteristics in distorted regions [9]–[14]. However, recent deep learning based approaches for fingerprint restoration utilize encoder-decoder based models [15]–[21]. A rigorous survey discussing approaches for fingerprint restoration methods is provided in [22]. However, the motivation for this paper arises from the observation that most deep learning based approaches for fingerprint restoration [15]–[21] rely only on convolution operations to understand the spatial context in a fingerprint image and explicit introduction of an additional task that mandates learning of spatial context can further improve the restoration performance. Recently, solving jigsaw puzzles has emerged as a highly useful self-supervised task to learn the spatial correlation between image patches and improve the generalization ability of a deep model [23].

Research Contributions: We introduce *rearrangement of jigsaw puzzles* as an effective task for fingerprint restoration models to enforce learning of *spatial context* in fingerprint images. To the best of our knowledge, CA-GAN is the introductory research that uses the principle of learning spatial context through solving jigsaw puzzles to boost the generalization ability of a fingerprint restoration model.

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TABLE 1. Comparison of average fingerprint quality scores achieved on [2] by CA-GAN and state-of-the-art.

Restoration Algorithm	Quality Score (↓)
Raw Image	2.94
Hong *et al.* [9]	2.05
DeconvNet [15]	1.95
Cycle-GAN [16]	1.76
MU-GAN [21]	1.33
FP-E-GAN [18]	1.31
CDC-GAN [3]	1.30
DU-GAN [19]	**1.26**
CA-GAN	1.29

TABLE 2. Comparison of EER achieved on [2] by CA-GAN and state-of-the-art.

Restoration Algorithm	Bozorth (↓)	MCC (↓)
Raw Image	16.36	13.23
Cycle-GAN [16]	29.52	27.96
Hong *et al.* [9]	11.01	11.46
DeConvNet [15]	10.93	10.86
FP-E-GAN [18]	7.30	5.96
CDC-GAN [3]	5.89	5.38
DU-GAN [19]	7.13	5.13
MU-GAN [21]	7.46	5.06
CA-GAN	**5.64**	**4.94**

II. PROPOSED METHOD

This section introduces *context-aware GAN (CA-GAN)*, a multi-task learning based fingerprint restoration model that given a noisy fingerprint image, is trained to generate a fingerprint with improved clarity of ridge structure. As an additional task, the model is trained to learn the spatial context in fingerprint images by solving jigsaw puzzles. Figure 2 presents the flowchart of CA-GAN. We now describe the task of solving a jigsaw puzzle. To create a jigsaw puzzle, the fingerprint image is decomposed into a grid of 3×3 patches. Although 9! random permutations exist to arrange these patches, however, to ensure no ambiguity in the task, a permutation set is defined, which contains a total of 30 elements where each element defines a unique permutation [23]. The choice of these 30 permutations is made by using a hamming distance based greedy algorithm as defined in [24]. Given a set of input fingerprint image patches, the model has to predict the correct permutation order. Subsequently, solving the jigsaw puzzle is formalized as a 30-class classification task.

Let us assume that ϕ and δ denote the respective parameters till the second last layer and the last layer of the fingerprint restoration model. To solve a given jigsaw puzzle, a new classification branch characterized by model parameters ζ is introduced to classify the correct order of a given permutation of image patches as one of the 30 classes. f denotes the deep model. The loss function optimized by CA-GAN is as follows:

$$\arg\min_{\phi,\delta,\zeta} \sum_{i=1}^{N} \mathcal{L}_{res}(f(x_i|\phi,\delta), y_i) + \sum_{k=1}^{K} \mathcal{L}_{jig}(f(z_k|\phi,\zeta), l_k)$$

L_{res} ensures that reconstructed fingerprint $f(x_i|\phi,\delta)$ generated for a given input fingerprint x_i is close to the ground truth, y_i. $\mathcal{L}_{jig}$ is a cross-entropy loss which ensures that predicted permutation label $f(z_k|\phi,\zeta)$ for input grid of patches (z_k is close to the true permutation label, l_k. N and K denote the number of labelled training images and the number of grids with reordered patches, respectively. Backbone network architecture and L_{res} are taken from [18].

Implementation Details: CA-GAN is trained on synthetically distorted fingerprints and the corresponding restored fingerprints [25]. The training data is prepared as per the guidelines provided in [18], [26]. CA-GAN is trained on a system comprising E5-2620v4 CPU and four NVIDIA GTX 1080 Ti GPUs. Each GPU has 11 GB RAM. CA-GAN is implemented using PyTorch, v1.11.0 and exploits Adam optimizer with a learning rate of 0.0002.

TABLE 3. Comparison of average fingerprint quality scores achieved on [1] by CA-GAN and state-of-the-art.

Restoration Algorithm	Quality Score (↓)
Raw Image	4.96
Cycle-GAN [16]	4.90
DeConvNet [15]	4.09
DU-GAN [19]	3.01
MU-GAN [21]	**1.48**
CDC-GAN [3]	2.38
CA-GAN	2.03

TABLE 4. Comparison of rank-50 accuracy achieved on [1] by CA-GAN and state-of-the-art.

Restoration Algorithm	Bozorth (↑)	MCC (↑)
Raw Image	5.45	6.06
Cycle-GAN [16]	6.29	4.65
DeConvNet [15]	14.02	14.27
Svoboda *et al.* [27]	NA	22.36
DU-GAN [19]	23.16	27.21
MU-GAN [21]	25.09	28.61
CDC-GAN [3]	28.00	33.09
CA-GAN	**28.24**	**34.59**

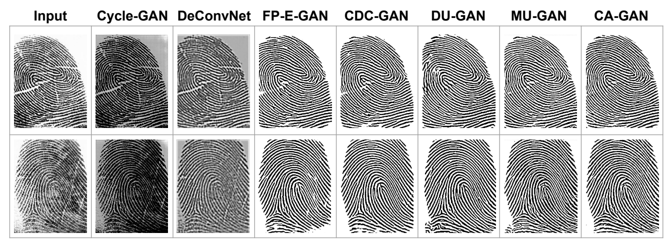


Fig. 3. Sample restored rural Indian fingerprints obtained using state-of-the-art and CA-GAN. Smoothest fingerprints with the best ridge-valley clarity are generated using the proposed CA-GAN.

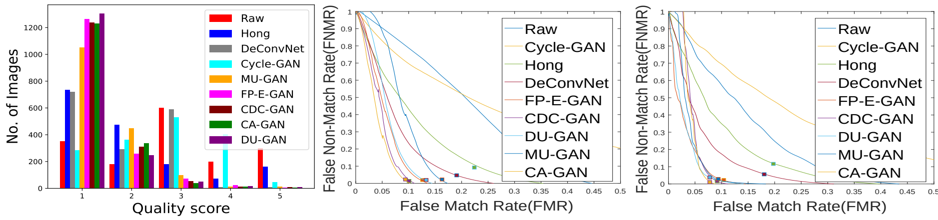
III. RESULTS AND ANALYSIS

A. Restoration of Fingerprints of Rural Indian Population

We initiate the analysis of fingerprint restoration performance on challenging rural Indian fingerprint dataset [2]. This dataset contains 1625 challenging fingerprints collected using an optical sensor from volunteers living in the rural India [2]. The restored fingerprints obtained using the proposed CA-GAN have superior ridge-valley clarity and smoother ridge structure (see Figure 3). On quantitative analysis, we find that better fingerprint quality (see Table 1) and comparison results (quantified by average equal error rate (EER)) for both Bozorth [28] and MCC matcher [29]–[31] (see Table 2) is obtained on restored fingerprints, which demonstrates the effectiveness of exploiting spatial context by solving jigsaw puzzles. Fingerprint quality results are illustrated through histogram while the comparison scores are presented through the detection error trade-off (DET) curves. All the plots corresponding to the rural Indian fingerprints [2] are plotted in Figure 4.

B. Restoration of Latent Fingerprints

Next experiment assesses CA-GAN on challenging latent fingerprints obtained from the IIITD-MOLF dataset [1]. This dataset constitutes 4400 challenging latent fingerprints that are matched across a gallery of live-scan fingerprints obtained using the Lumidigm sensor [1]. Sample restored fingerprints obtained for input latent fingerprints of IIITD-MOLF dataset [1] are presented in Figure 5. We observe that while state-of-the-art generates spurious ridge structure in smudged fingerprint regions, CA-GAN, on the other hand, successfully predicts ridge details in such distorted regions. Subsequently, CA-GAN generates superior quality fingerprints (see Table 3) that obtain better matching performance (see Table 4). For latent fingerprints, the comparison performance is presented through



(a) (b) (c)

Fig. 4. (a) Fingerprint quality values obtained on the rural Indian fingerprints [2] and the DET curves corresponding to fingerprint comparison tools (b) Bozorth and (c) MCC.

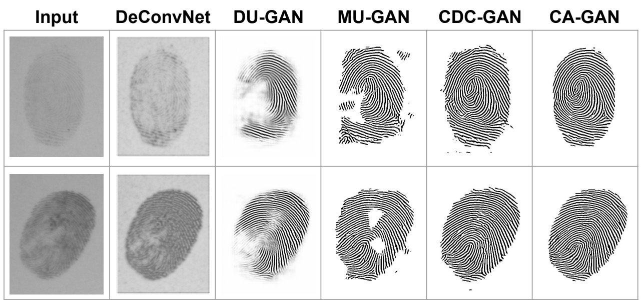


Fig. 5. Sample restored fingerprints obtained for latent fingerprints.

TABLE 5. Comparison of average fingerprint quality values obtained for jigsaw puzzle versus standard self-supervised tasks.

Restoration Algorithm	Quality Score (↓)
Baseline	1.31
Location	1.30
Rotation	1.37
CA-GAN	**1.29**

TABLE 6. Average EER obtained for jigsaw puzzle versus standard self-supervised tasks.

Restoration Algorithm	Bozorth (↓)	MCC (↓)
Baseline	7.30	5.96
Location	6.60	5.88
Rotation	6.15	5.48
CA-GAN	**5.64**	**4.94**

cumulative matching characteristics (CMC) curves. All the plots corresponding to latent fingerprints [1] are presented in Figure 6.

C. Capability to Preserve Ridge Details

Next, we work towards quantifying the capability of CA-GAN to preserve ridge details. For this experiment, we simulate poor quality fingerprints by adding noise into good quality fingerprints [26]. Sample restored fingerprints generated using CA-GAN for given simulated poor quality fingerprints are illustrated in Figure 7 (a). Groundtruth is obtained by binarizing the good quality fingerprint using NBIS [28]. Later, SSIM is computed among the target binarized fingerprint and the restored fingerprint achieved using CA-GAN. High SSIM scores are obtained, which demonstrate the ability of CA-GAN to retain ridge structure while restoring it.

D. Comparison with Standard Self-supervision tasks

Lastly, to demonstrate the significance of learning *spatial context* by solving jigsaw puzzles. For this, we compare the restoration ability obtained after introducing the self-supervised task of solving a jigsaw puzzle [23] versus two standard self-supervised tasks: prediction of rotation [32] and location [33]. Results reveal that learning spatial context through solving jigsaw puzzles turns out to be more effective than learning to predict rotation or location as it renders better fingerprint quality scores(see Table 5) and matching performance (see Table 6). Sample restored fingerprints are presented in Figure 7 (b) while histogram of quality scores and DET curves are presented in Figure 8.

IV. CONCLUSION

This paper introduces solving jigsaw puzzles to learn the spatial context in fingerprint images. Improved fingerprint recognition results are obtained on fingerprints reconstructed by CA-GAN, which confirms that learning of spatial context improves the generalization ability of the fingerprint restoration model. In the future, learning of jigsaw puzzles can be explored to improve the generalizability of deep learning based presentation attack detectors and region of interest segmentation networks.

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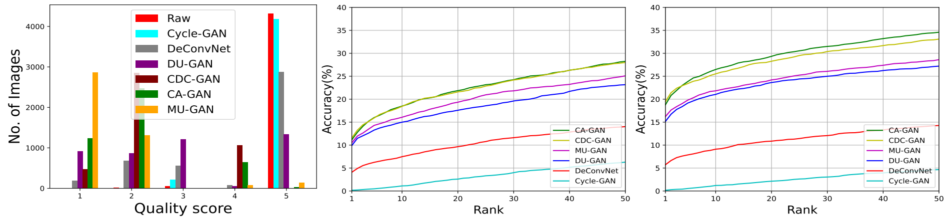

Fig. 6. (a) Fingerprint quality values obtained on latent fingerprints [1] and the CMC curves corresponding to fingerprint comparison tools (b) Bozorth and (c) MCC.

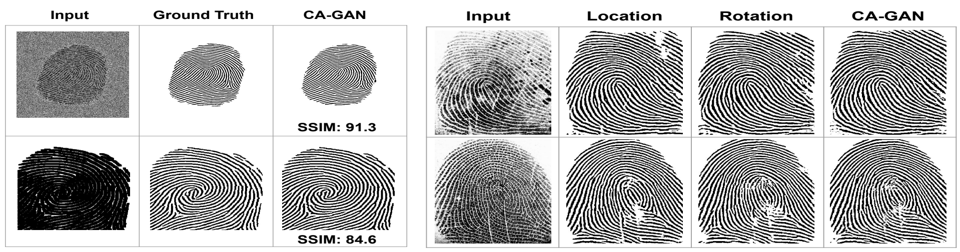

Fig. 7. Sample cases demonstrating (a) the ridge preservation ability of CA-GAN (b) superior performance of CA-GAN by solving jigsaw puzzles compared to classical self-supervised tasks of rotation and location prediction.

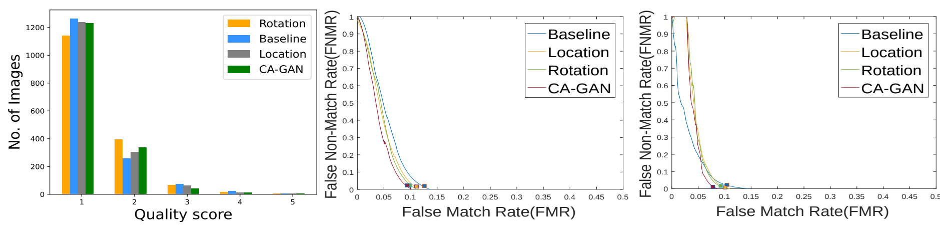

Fig. 8. (a) Fingerprint quality values obtained for different choices of self-supervised tasks and the DET curves corresponding to fingerprint comparison tools (b) Bozorth and (c) MCC. Learning spatial context via solving jigsaw puzzles turns out to be the most effective choice.

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