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Local Distributional Smoothing for Noise-invariant Fingerprint Restoration

Abstract: Existing fingerprint restoration models fail to generalize on severely noisy fingerprint regions. To achieve noise-invariant fingerprint restoration, this paper proposes to regularize the fingerprint restoration model by enforcing *local distributional smoothing* by generating similar output for clean and perturbed fingerprints. Notably, the perturbations are learnt by virtual adversarial training so as to generate the most difficult noise patterns for the fingerprint restoration model. Improved generalization on noisy fingerprints is obtained by the proposed method on two publicly available databases of noisy fingerprints.

Keywords: Fingerprints, Denoising, Biometrics.

1 Introduction and Related Work

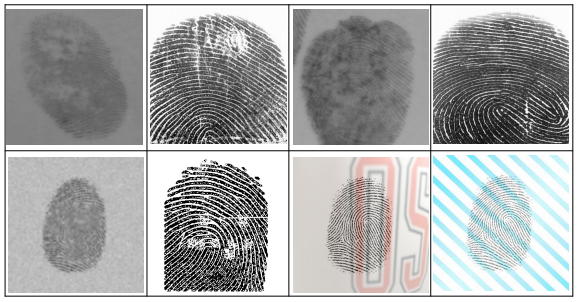


Fig. 1: Different conditions that prevail while acquiring fingerprints result in different kinds of noise patterns (top row). Additionally, training on noisy synthetic fingerprints (source domain) and testing on real noisy fingerprints (target domain) also hampers generalization on noisy (target) fingerprints due to the *domain shift* between the two domains (bottom row).

Fingerprints are among the most frequently adopted biometric trait for numerous applications involving human recognition [GPM20, Jo21e, Jo22a, Jo22c, Jo22e, Joed, Jo21a]. For fingerprint recognition to work satisfactorily on noisy fingerprints, a *fingerprint restoration model* is required as it is responsible for enhancing the clarity of ridges and valleys and estimating the missing ridge information due to smudging, occlusion, or damp and dry fingers. One of the difficulties in training a fingerprint restoration model is the unavailability of labelled training set of noisy and respective restored fingerprints. To mitigate this difficulty, the restoration model is trained on noisy synthetic fingerprints whose good-quality binarized fingerprints are available as labels. However, this leads to poor generalization on real noisy fingerprints due to the *domain shift* between training (source) and test (target) databases (see Figure 1). Furthermore, as fingerprints can be acquired either voluntarily or involuntarily, different conditions can prevail during acquisition. Subsequently, a range

of different noise patterns is observed for fingerprints, making it difficult for fingerprint restoration to generalize on noisy fingerprints.

This paper addresses the challenges in noise-invariant fingerprint restoration by introducing *Virtual Adversarially Trained Generative Adversarial Network (VAT-GAN)*. VAT-GAN is a generative adversarial network (GAN) that is trained to enforce *local distributional smoothing* in both source and target domains such that the fingerprint restoration model must generate similar outputs for clean and perturbed variants of a given fingerprint image. Notably, the perturbations are learnt through virtual adversarial training (VAT) [Mi18, Mo22] to generate the most difficult noise patterns for the fingerprint restoration model.

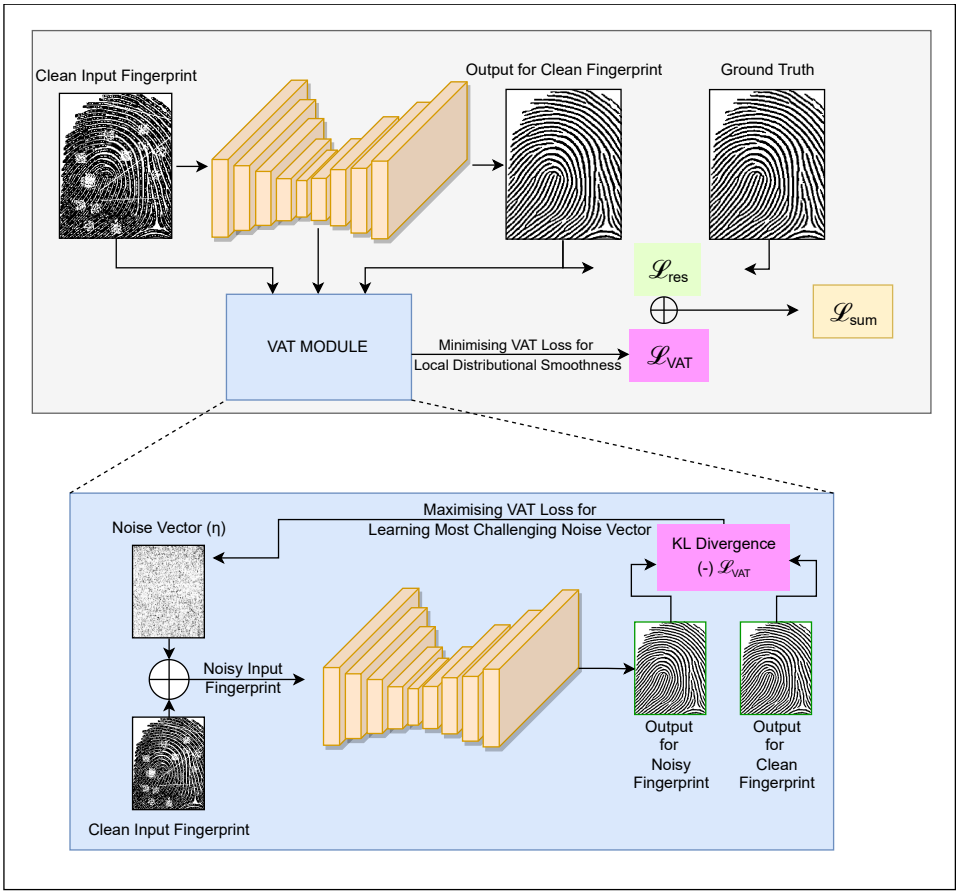


Fig. 2: VAT-GAN leverages *supervised fingerprint restoration loss* ($\mathscr{L}_{res}$) to learn transformation from synthetic noisy (source) fingerprints to improved quality fingerprints. Furthermore, to impose noise-invariant restoration, an *unsupervised virtual adversarial training loss* ($\mathscr{L}_{VAT}$) is exploited for learning to generate similar output for clean and noisy variants of a given input fingerprint (from both target and source domain). Notably, the most challenging noise is learnt in a virtually adversarial manner.

Traditional fingerprint restoration methods utilize context [Li22], for instance, ridge orientations [Gu20] for estimating ridge details in noisy regions. Both spatial domain filtering [HWJ98] and frequency domain filtering [CCG07] are among the most popular traditional fingerprint restoration methods. Recent methods for fingerprint restoration utilize deep models with encoder-decoder architecture for fingerprint restoration [SSB16, Jo21b, Ka20, Jo21c, Jo19, Jo21d, QLL19, Jo22d]. However, as also mentioned before, these deep models are trained on noisy synthetic fingerprints while tested on real noisy fingerprints [SSB16, Ka20, Jo21c, Jo19, Jo21d, Jo22b, QLL19, Jo22d], which hampers their ability to generalize on different noise patterns encountered in real noisy fingerprints.

Research Contributions: To ensure noise-invariant fingerprint restoration, we introduce *VAT-GAN* that enforces *local distributional smoothing* by enabling similar outputs for perturbed and clean fingerprints. This is introductory research that incorporates virtual adversarial training (VAT) in the fingerprints domain to facilitate noise-invariant restoration. To alleviate the domain shift, VAT is introduced in both source and target domains. Furthermore, we provide a peak on the improved generalization by performing an ablation study to quantify the effect of introducing VAT on the source and target domains. Lastly, an extensive comparison with state-of-the-art fingerprint restoration methods and adversarial training methods is also provided.

2 Proposed Method

VAT-GAN is a fingerprint restoration method that employs a deep encoder-decoder network design to transform a noisy fingerprint into an enhanced quality fingerprint. Here the quality is quantified in terms of ridge smoothness and clarity, eventually resulting in improved recognition. VAT-GAN employs *virtual adversarial training* (VAT) [Mi18] to provide generalization over different noise patterns originating due to different acquisition conditions. To be specific, VAT-GAN not only utilizes a supervised loss (L_{res}), as defined in [Jo19], to learn fingerprint restoration. However, we also introduce an unsupervised virtual adversarial training loss ($\mathscr{L}_{VAT}$) while training VAT-GAN. $\mathscr{L}_{VAT}$ ensures *local distributional smoothness* so that the model outputs similar restored fingerprints for clean and noisy variants of a given input fingerprint. Noise (η) in the case of VAT is adversarially learnt such that the most challenging noise samples are obtained to learn noise-invariant restoration. Furthermore, to tackle domain shift between real (target domain) fingerprints and synthetic noisy (source domain) fingerprints, $\mathscr{L}_{VAT}$ is introduced in both domains. The flowchart of VAT-GAN is demonstrated in Figure 2.

Mathematically, assume D_s and D_t denote the annotated source database and unannotated target database, respectively. $D_s = \{(d_s, y_s)\}$ and $D_t = \{d_t\}$. The restored fingerprint obtained using VAT-GAN is denoted by $p(d_s)$. $D_{un} = \{(d_t \in D_t) \cup (\hat{d_s} \in D_s)\}$, where $\hat{d_s}$ denotes the input sample from source domain without annotation and $\mathscr{KL}$ denotes KL divergence.

$$\mathscr{L}_{res}(D_s) = \sum_{(d_s, y_s) \in D_s} L_{res}(p(d_s), y_s) \tag{1}$$

$$\mathscr{L}_{VAT}(D_{un}) = \mathscr{K}\mathscr{L}(d_{un} + \eta || d_{un}) \tag{2}$$

$$\eta = \arg\max_{\hat{\eta}} \{\mathscr{L}_{res}(d_{un}, d_{un} + \hat{\eta})\} \tag{3}$$

$$\mathscr{L}_{sum} = \mathscr{L}_{res}(D_s) + \mathscr{L}_{VAT}(D_{un}) \tag{4}$$

VAT-GAN is built over a ResNet backbone based GAN [Jo19] and trained on four NVIDIA GTX 1080 Ti GPUs. VAT-GAN is implemented in Pytorch and optimized via Adam optimizer while utilizing two images per batch.

3 Results and Analysis

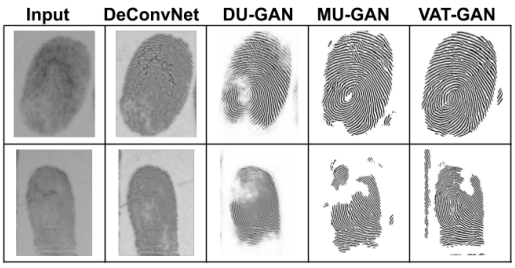


Fig. 3: Examples of noisy latent fingerprints [SVS15] being better restored around severely degraded regions by VAT-GAN than existing restoration methods.

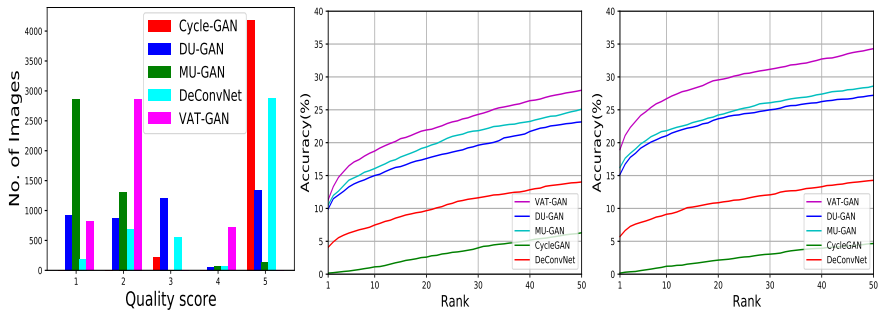


Fig. 4: Restoration results on [SVS15] signifying superiority of VAT-GAN: (a) Quality values quantified by *Nfiq* [NI]; Recognition results acquired from open-source fingerprint recognition tools (b) Bozorth (c) MCC.

3.1 Results on Noisy Latent Fingerprints

VAT-GAN is first evaluated on the IIITD-MOLF database [SVS15]. This database contains the largest amount of latent fingerprint impressions (4400). The gallery that we use

Tab. 1: Quality values attained on [SVS15].

Restoration Technique	Quality Value (↓)
Raw Image	4.96
Cycle-GAN [Ka20]	4.90
DeConvNet [SSB16]	4.09
DU-GAN [Jo21d]	3.01
MU-GAN [Jo22d]	**1.48**
VAT-GAN	2.14

Tab. 2: Rank-50 accuracy obtained on the IIITD-MOLF database [SVS15].

Restoration Technique	Bozorth (↑)	MCC (↑)
Raw Image	5.45	6.06
Cycle-GAN [Ka20]	6.29	4.65
DeConvNet [SSB16]	14.02	14.27
Svoboda *et al.* [SMB17]	NA	22.36
DU-GAN [Jo21d]	23.16	27.21
MU-GAN [Jo22d]	25.09	28.61
VAT-GAN	**27.97**	**34.30**

for experiments is acquired from the fingerprint reader Lumidigm. Figure 3 presents the superior performance of VAT-GAN around smudged and poor contrast regions compared to existing methods. Superior quality values attained using *nfiq* [NI] (Table 1) and recognition results on both Bozorth [NI] and the MCC matcher [CFM10, FM10, FMC12] are reported for VAT-GAN (Table 2). The corresponding graphs are illustrated in Figure 4. These findings illustrate the superior restoration ability of VAT-GAN compared to existing fingerprint restoration methods.

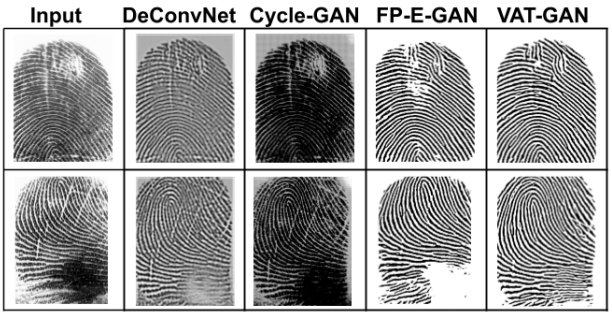


Fig. 5: Examples of noisy rural Indian fingerprints [Pu10] that are better restored by VAT-GAN than existing restoration methods.

3.2 Results on Noisy Rural Indian Fingerprints

We continue the evaluation of VAT-GAN on the Rural Indian fingerprint database [Pu10] containing challenging 1631 fingerprints obtained from rural Indians that perform a lot of physical labor. Figure 5 presents that VAT-GAN enhances ridge-valley contrast and approximates ridge details around cuts and creases, thereby improving quality value (Table 3) and eventually, an improved recognition performance as well (Table 4).

Tab. 3: Quality values attained on [Pu10].

Restoration Technique	**Quality Value (↓)**
Raw Image	2.94
Hong *et al.* [HWJ98]	2.05
DeconvNet [SSB16]	1.95
Cycle-GAN [Ka20]	1.76
FP-E-GAN [Jo19]	**1.31**
VAT-GAN	1.32

Tab. 4: Equal error rate obtained on an average on [Pu10].

Restoration Technique	**Bozorth (↓)**	**MCC (↓)**
Raw Image	16.36	13.23
Hong *et al.* [HWJ98]	11.01	11.46
DeConvNet [SSB16]	10.93	10.86
Cycle-GAN [Ka20]	29.52	27.96
FP-E-GAN [Jo19]	7.30	5.96
VAT-GAN	**6.30**	**5.75**

Tab. 5: Quality values attained for different adversarial training methods.

Restoration Technique	**Quality Value (↓)**
Baseline	**1.31**
FGSM-GAN	1.33
PGD-GAN	1.34
VAT-GAN	1.32

Tab. 6: Equal error rate obtained on an average on different adversarial training methods.

Restoration Technique	**Bozorth (↓)**	**MCC (↓)**
Baseline	7.30	5.96
PGD-GAN	9.46	9.07
FGSM-GAN	6.39	6.04
VAT-GAN	**6.30**	**5.75**

3.3 Comparison with State-of-the-art Adversarial Training Methods

In this subsection we justify the choice of virtual adversarial training (VAT) [Mi18] over other state-of-the-art adversarial training methods. For this, we exploit two state-of-the-art adversarial training methods, namely, fast gradient sign method (FGSM) [GSS15] and projected gradient descent (PGD) [Ma17] over the backbone FP-E-GAN. We refer to the resulting fingerprint restoration models as FGSM-GAN and PGD-GAN, respectively. We find that PGD does not generalize to fingerprints, while VAT outperforms FGSM (see Table 5 and Table 6) and therefore, turns out to be a better choice for the fingerprint restoration backbone.

3.4 Capability to Preserve Ridge Details

A fingerprint restoration method must preserve details about ridge structure, e.g., orientation and minutiaes. The next experiment is dedicated to demonstrating the capability of VAT-GAN to preserve details about ridge structure while restoring a given fingerprint. In Figure 6 (a), we show sample restored fingerprints obtained for noisy synthetic fingerprints. The restored fingerprint is also compared with the ground truth, and a high SSIM

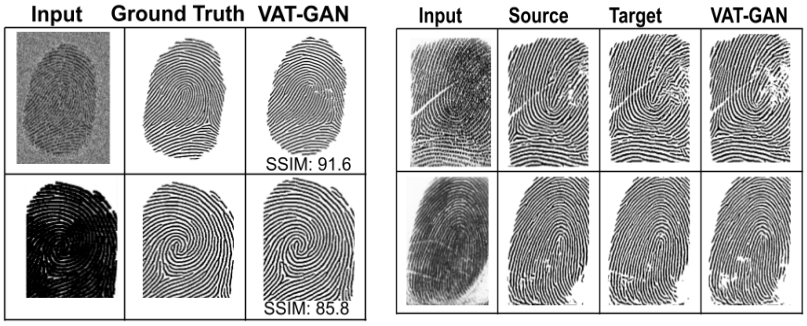
Tab. 7: Quality values attained on different variants.

Restoration Technique	**Quality Value (↓)**
Baseline	1.31
Source	**1.29**
Target	1.33
VAT-GAN	1.32

Tab. 8: Equal error rate obtained on an average on different variants.

Restoration Technique	**Bozorth (↓)**	**MCC (↓)**
Baseline	7.30	5.96
Source	6.74	6.09
Target	6.53	5.97
VAT-GAN	**6.30**	**5.75**

(structural similarity index metric) value is obtained between the two. The high SSIM value verifies the capability of VAT-GAN to preserve details about ridge structure.



(a) (b)

Fig. 6: Examples signifying (a) superior capability of VAT-GAN to preserve ridge information (b) impact of enforcing invariance to virtual adversarial noise in target and source domains.

3.5 Ablation Study

We conclude the analysis of VAT-GAN by performing an ablation study with a motivation to get insights into establishing local distributional smoothness separately in the source and target domain, respectively. As expected, enforcing local distributional smoothness in either domain improves better restoration performance. However, as expected, imposing local distribution smoothness in the target domain results in more effective restoration than imposing it in the source domain. The results make sense as else the samples in the target domain are unrevealed to the fingerprint restoration model. Again, as expected, the best restoration performance is obtained by VAT-GAN when local distributional smoothness is imposed in both domains since it provides additional information about the target domain and helps to reduce the *domain gap* between the two domains. However, we find that values of fingerprint quality are improved only incrementally. Figure 6 (b) illustrates examples comparing the contribution of imposing local distributional smoothness in each domain, while recognition results are provided in Table 7 and Table 8.

4 Conclusion and Future Work

This research proposes a noise-invariant fingerprint restoration method that enforces *local distributional smoothness* by predicting similar output for clean and noisy variants of a given input fingerprint. Notably, the invariance is enforced over the most challenging noise learnt through *virtual adversarial training*. Results reveal the superior noise-invariant restoration ability of the proposed method when compared against existing methods for fingerprint restoration. Future research can extend the idea of imposing local distributional smoothing through VAT in fingerprint segmentation or detecting presentation attacks.

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