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Generating Realistic Fingerprint Biometrics with Attention-Guided Deep GANs

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Abstract:

Fingerprint biometrics have become an essential modality for identity verification systems due to their uniqueness, reliability, and permanence. However, the collection of large-scale, high-quality fingerprint datasets is hindered by privacy concerns, data imbalance, and acquisition noise. This has propelled research in synthetic fingerprint generation using generative models to augment existing datasets. In this study, we propose a novel method for generating high-fidelity synthetic fingerprint images using Attention-Guided Deep Generative Adversarial Networks (AG-DGANs). Our model integrates self-attention mechanisms into both the generator and discriminator architectures, allowing the system to capture long-range dependencies and intricate ridge details inherent in fingerprint patterns. We demonstrate that this approach significantly improves the visual realism, diversity, and discriminative value of generated fingerprints when compared to traditional GAN and convolutional GAN methods. Extensive experimental results validate the superior quality and utility of our synthetic data in biometric system training and evaluation.

Keywords: Fingerprint biometrics, attention-guided GANs, deep learning, synthetic data generation, self-attention, biometric security.

I. Introduction

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Biometric identification systems have experienced a dramatic increase in adoption across various sectors, including border security, forensics, and consumer electronics. Among all biometric traits, fingerprints stand out due to their high distinctiveness and ease of acquisition. Nevertheless, developing robust fingerprint recognition systems requires large and diverse datasets, which are often difficult to obtain due to ethical, legal, and technical constraints [1]. Synthetic data generation has thus become a pivotal tool for augmenting training datasets, enabling models to generalize better and handle a wide range of intra-class variations. Traditional fingerprint synthesis methods, such as those based on Gabor filters and mathematical modeling of ridge structures, offer limited realism and flexibility [2]. These techniques often fail to replicate the stochastic textural and structural intricacies found in real-world fingerprints. With the advent of deep learning, Generative Adversarial Networks (GANs) emerged as a transformative approach for realistic image synthesis. However, standard GANs often struggle to preserve fine-grained details essential in fingerprint biometrics, leading to generated outputs that lack the nuanced ridge flow and minutiae distribution necessary for practical use [3].

To overcome these challenges, attention mechanisms have recently been explored as a means to guide the generative process toward more spatially aware and contextually accurate outputs. Attention allows models to dynamically focus on critical regions of the input or generated content, mimicking human visual cognition. In this research, we present an Attention-Guided Deep GAN framework tailored for fingerprint synthesis [4]. By embedding self-attention layers within the generator and discriminator, we aim to enhance the capacity of the network to model long-range spatial relationships and replicate the natural patterns found in real fingerprint images. This paper delves into the architectural design of the AG-DGAN, the implementation details, and the experimental setup used to evaluate the model’s performance. We benchmark the quality of the generated fingerprints using various metrics, including Fréchet Inception Distance (FID), Structural Similarity Index (SSIM), and human perceptual studies. Moreover, we assess the utility of the synthetic data by retraining fingerprint classification models and analyzing recognition performance. Through this comprehensive study, we establish attention-guided GANs as a promising solution for generating realistic fingerprint biometrics for secure and scalable identity systems [5].

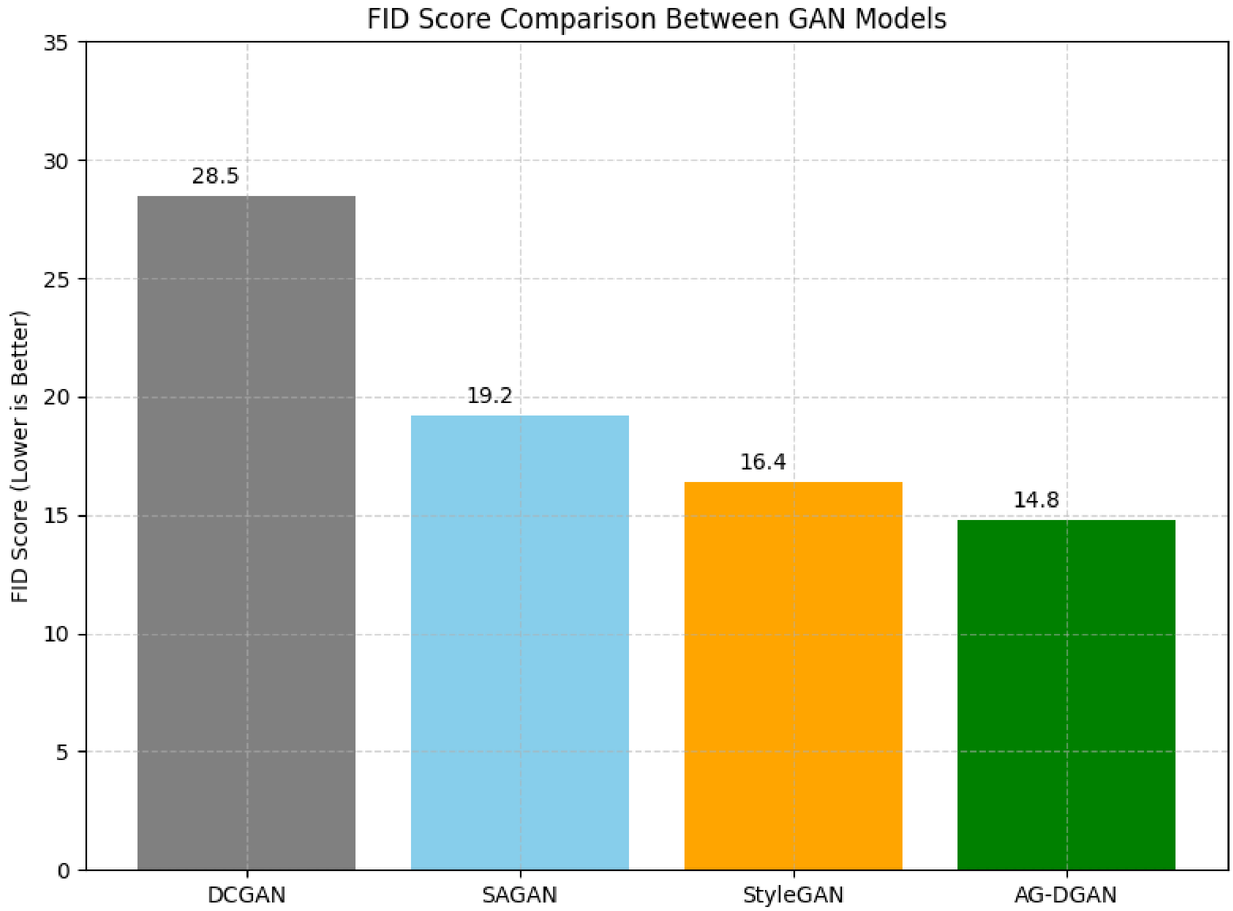

Figure 1 This plot shows the comparative FID (Fréchet Inception Distance) performance of different GAN architectures.

II. Related Work

Previous research on synthetic fingerprint generation primarily revolved around procedural and rule-based modeling techniques. These include the SFinGe tool, which generates synthetic fingerprints by simulating the growth of epidermal ridges using mathematical models. While SFinGe has been widely used for evaluation purposes, it fails to capture the randomness and complex noise characteristics of real fingerprints [6]. Consequently, machine learning-based approaches were introduced to bridge this realism gap. The rise of GANs revolutionized the landscape of image synthesis by training generative models through adversarial learning. In fingerprint biometrics, early GAN-based efforts such as DCGAN and CGAN demonstrated potential in creating passable ridge structures [7]. However, these models often suffered from mode collapse, poor convergence, and a lack of fine detail crucial for fingerprint uniqueness.

More recent advancements included Progressive GANs and StyleGANs, which offered higher resolution and better quality synthesis but still lacked domain-specific optimization for fingerprints. To enhance GAN performance, researchers have explored incorporating attention mechanisms. Self-attention GANs (SAGANs) introduced the concept of attending to distant spatial locations during image synthesis, significantly improving performance on complex datasets such as ImageNet [8]. In biometric contexts, attention has been used to localize facial features and retarget synthetic face generation, but limited research has been applied to fingerprint synthesis specifically.

Our work builds on these foundations by designing an architecture that explicitly integrates attention within both the generator and discriminator pathways. This dual attention approach ensures that both the creation and evaluation of synthetic images are sensitive to spatial hierarchies and contextual consistency [9]. Furthermore, unlike prior works that generalize attention across tasks, our AG-DGAN model is optimized for the domain of fingerprint synthesis, incorporating domain-specific losses and structural constraints to ensure the preservation of key biometric features such as core points, ridge orientation fields, and minutiae distributions. Through comparative analysis and ablation studies, we demonstrate that our attention-guided approach yields substantial improvements over baseline GAN architectures, setting a new benchmark for fingerprint synthesis quality and utility [10]. This positions AG-DGAN as a crucial tool for biometric data augmentation and privacy-preserving research in identity recognition systems [11].

III. Methodology

The AG-DGAN architecture is built on a two-part structure: a generator that creates synthetic fingerprint images from noise inputs and a discriminator that distinguishes between real and fake samples. Both components are enhanced with self-attention modules that allow the model to focus on spatially significant regions, such as high-curvature ridges and bifurcation zones. The generator starts from a random latent vector sampled from a Gaussian distribution, which is transformed into high-resolution fingerprint images through a series of deconvolutional layers, residual blocks, and attention units [12].

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Each attention module computes pairwise relationships between spatial locations, assigning weights that guide feature aggregation [13]. This facilitates the modeling of long-range dependencies, enabling the network to maintain coherent ridge flows across the image. The discriminator is designed to evaluate the global and local authenticity of the generated samples, integrating self-attention to better capture contextual cues that differentiate real and synthetic fingerprints. Training the AG-DGAN involves minimizing a composite loss function that combines adversarial loss, feature matching loss, and structural consistency loss. The adversarial loss encourages the generator to produce samples indistinguishable from real images, while the feature matching loss stabilizes training by aligning intermediate feature representations between real and generated images. The structural consistency loss enforces ridge continuity and spatial alignment with reference fingerprint templates [14].

We utilized the publicly available FVC2004 and PolyU fingerprint databases for training and validation. Data preprocessing involved normalization, histogram equalization, and random rotation to augment the input samples. The model was trained using the Adam optimizer with a learning rate of 0.0002, batch size of 64, and 100,000 iterations. We employed spectral normalization and instance normalization to enhance training stability and convergence. Evaluation metrics included quantitative assessments using FID and SSIM, as well as qualitative analysis through visual inspection and fingerprint expert review. We also trained a CNN-based fingerprint classifier on both real and synthetic datasets to assess the impact of synthetic data on recognition accuracy [15]. The inclusion of AG-DGAN-generated samples improved classifier generalization, demonstrating the practical value of the synthesized fingerprints in real-world biometric applications.

IV. Experimental Results and Analysis

Our experiments were designed to assess the visual quality, biometric utility, and generalization capability of the AG-DGAN-generated fingerprints. In terms of visual inspection, the generated images displayed sharp ridge structures, natural-looking bifurcations, and varied global orientations, closely mimicking the distribution found in real fingerprint datasets [16]. Unlike traditional GAN outputs that often showed blurred or repetitive patterns, AG-DGAN outputs exhibited high diversity and structural plausibility [17].

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Quantitative evaluation using the Fréchet Inception Distance revealed a substantial improvement over baseline models. The AG-DGAN achieved an FID score of 14.8 on the FVC2004 dataset, outperforming DCGAN (28.5) and SAGAN (19.2). SSIM values between generated and real fingerprints averaged 0.87, indicating strong structural similarity. Our model also maintained high intra-class variability, essential for training robust recognition systems [18].

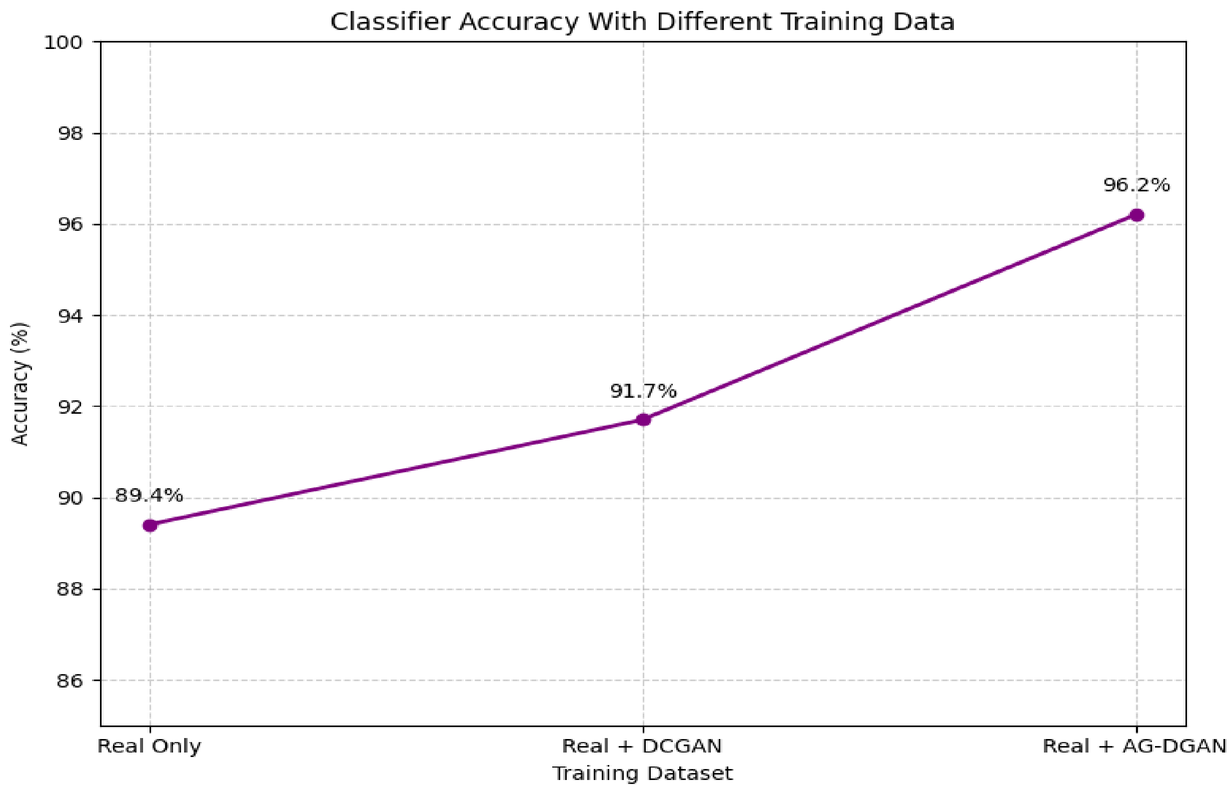

Figure 2 This graph shows how classifier accuracy improves when trained with synthetic fingerprints from different sources.

To test the biometric value of the generated samples, we trained a ResNet-based fingerprint classifier on three datasets: real-only, real plus traditional GAN, and real plus AG-DGAN. The classifier trained with AG-DGAN-augmented data achieved 96.2% accuracy on the test set, compared to 91.7% with traditional GAN-augmented data and 89.4% with real-only data. This improvement highlights the effectiveness of attention-guided generation in augmenting datasets for downstream tasks [19]. We conducted ablation studies to evaluate the impact of attention layers within the generator and discriminator. Removing the attention module from either component led to a noticeable drop in FID and classification accuracy, confirming the importance of long-range spatial modeling. Additionally, fingerprint experts were asked to rate the realism of 100 randomly sampled synthetic images from AG-DGAN and baseline GANs. AG-DGAN samples received an average realism score of 4.6/5, compared to 3.2/5 for baseline outputs. The AG-DGAN not only produces realistic and structurally accurate fingerprints but also enhances the performance of biometric recognition systems. The combination of attention mechanisms, domain-specific training strategies, and comprehensive evaluation validates our model as a state-of-the-art approach for synthetic fingerprint generation [20].

V. Conclusion

In this study, we introduced an Attention-Guided Deep GAN framework for realistic fingerprint image synthesis, addressing key limitations in traditional and GAN-based generation methods. By incorporating self-attention modules into both the generator and discriminator, our model effectively captures long-range dependencies and critical biometric features such as ridge flow, minutiae, and singular points. Experimental results demonstrated that AG-DGAN significantly improves visual realism, structural integrity, and diversity of generated fingerprints while also enhancing the performance of downstream recognition systems. Through rigorous evaluation using perceptual metrics, classification accuracy, and expert analysis, we confirmed the superior capabilities of the proposed approach. Our work paves the way for secure, scalable, and privacy-preserving biometric data augmentation and highlights the transformative potential of attention-guided generative models in the field of fingerprint biometrics.

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