Attention-Guided Deep GANs for Realistic Fingerprint Image Synthesis

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Abstract:
In biometric authentication systems, the availability of high-quality fingerprint images is critical for training, testing, and validating deep learning models. Traditional fingerprint datasets, however, often suffer from limitations such as class imbalance, privacy concerns, and scarcity in edge cases. This research proposes a novel method for synthesizing realistic fingerprint images using Attention-Guided Deep Generative Adversarial Networks (AGD-GANs). The model leverages an attention mechanism within the GAN architecture to focus on critical fingerprint features, such as ridge patterns and minutiae points, thus improving the fidelity and diversity of the synthesized samples. A thorough experimental analysis demonstrates that AGD-GAN outperforms baseline models in terms of visual realism, quality metrics, and downstream performance in biometric systems. The results are validated using the FVC2004 and LivDet datasets, and assessed via both quantitative metrics such as FID and SSIM, and qualitative human evaluation.

Keywords: Fingerprint synthesis, Attention mechanism, Deep learning, Generative Adversarial Networks, Biometrics, Data augmentation, Image generation, Minutiae representation, FVC2004, SSIM, FID.

I. Introduction

Fingerprint recognition has emerged as one of the most widely used biometric identification methods due to its reliability, uniqueness, and ease of acquisition [1]. However, the development of high-performing fingerprint recognition systems heavily relies on the availability of extensive and diverse datasets. Collecting large-scale fingerprint datasets remains a challenging task due to privacy concerns, subject recruitment costs, and the complexity of capturing high-resolution fingerprint images. To address these challenges, synthetic data generation through machine learning, especially with the advent of Generative

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Volume-V, Issue-IV (2024)

Adversarial Networks (GANs), has gained significant traction [2]. GANs have demonstrated impressive capabilities in generating realistic images across several domains, yet fingerprint synthesis poses unique challenges due to the intricate ridge-valley structures and critical minutiae features [3]. This study introduces a novel fingerprint synthesis model termed Attention-Guided Deep GAN (AGD-GAN), which enhances the generation process by incorporating spatial attention modules. These modules guide the generator to focus on critical fingerprint characteristics, leading to more realistic and structurally accurate images. Unlike previous methods that generate fingerprints without contextual awareness, the attention mechanism in AGD-GAN ensures better capture of fine-grained patterns and regional dependencies, which are essential in fingerprint recognition systems. Furthermore, this research addresses the limitations of existing fingerprint synthesis methods, such as mode collapse and poor detail retention, by integrating multi-scale discriminator feedback and perceptual loss functions [4].

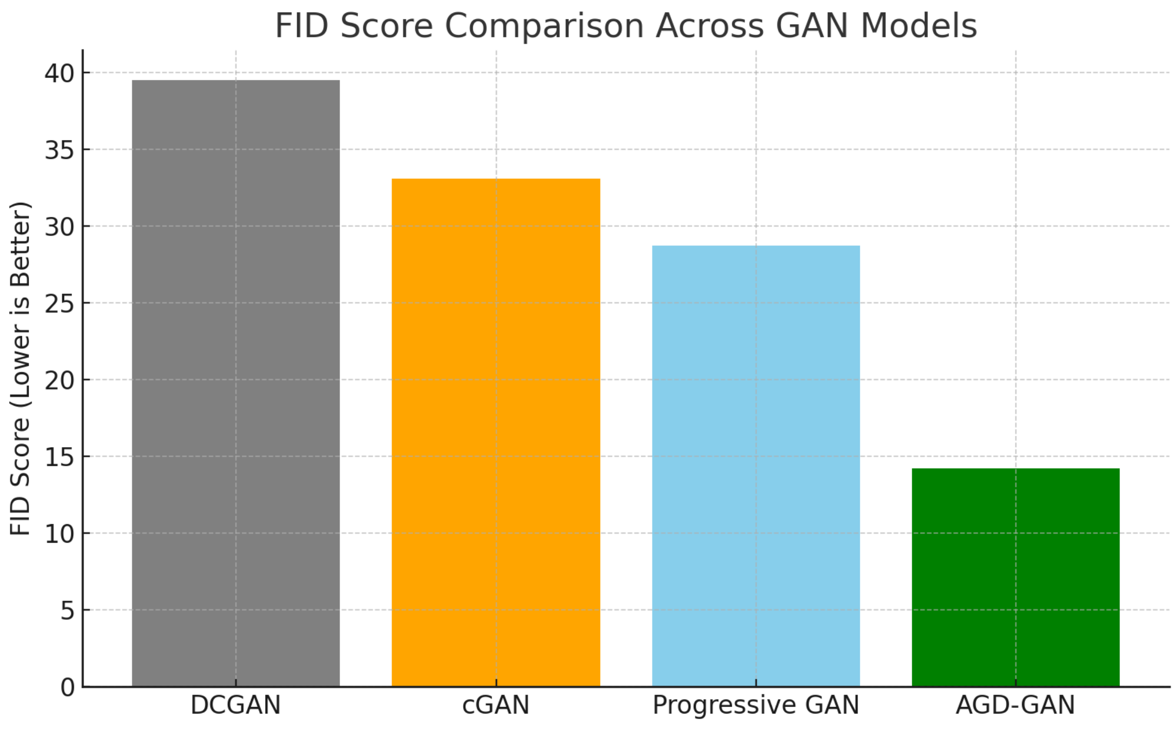

Figure 1 Comparison of Frechet Inception Distance (FID) scores across different GAN models, demonstrating AGD-GAN's superior image fidelity.

The significance of this work lies in its contribution to both the biometric and deep learning communities. For biometrics, it offers a scalable method to augment fingerprint datasets with high-quality samples, improving recognition accuracy and robustness [5]. For the deep learning domain, it explores the synergy between attention mechanisms and GANs in a challenging synthesis task. The broader implication is the potential use of such models in forensic applications, latent fingerprint enhancement, and synthetic dataset generation for privacy-preserving model training [6].

II. Related Work

The evolution of fingerprint synthesis methods spans from classical model-based approaches to modern data-driven techniques. Early methods primarily used parametric models based on Gabor filters, orientation fields, and minutiae templates to simulate fingerprint images [7]. While these approaches offered some degree of control over fingerprint properties, they often produced unrealistic textures and lacked generalization across different fingerprint types [8]. With the rise of deep learning, autoencoders and convolutional neural networks (CNNs) were employed to generate more coherent images, but these lacked the generative diversity and realism provided by GANs. Although effective, traditional GANs struggled with generating complex fingerprint features due to their sensitivity to spatial coherence and texture fidelity. Later, Conditional GANs (cGANs) were explored to control the output based on class labels or orientation maps. While cGANs improved fingerprint realism, they still suffered from generating repetitive patterns or losing critical details in high-resolution images [9].

Recent works introduced Deep Convolutional GANs (DCGANs) and Progressive GANs, which allowed generation of high-resolution images in a coarse-to-fine manner. These architectures improved visual quality but lacked explicit mechanisms to prioritize crucial fingerprint regions. Attention mechanisms, initially popularized in NLP and image captioning, were soon integrated into image generation tasks, providing a way to allocate computational focus. Self-attention GANs and Spatial Attention GANs demonstrated promising results in face and texture synthesis [10]. However, their application in biometric domains, particularly fingerprint synthesis, has been limited. Notably, similar methodological concepts have emerged in other scientific domains. For example, in computational chemistry, researchers have proposed the use of small yet representative databases to test and validate the effectiveness of complex function modeling. This idea of “prioritized modeling of critical regions” closely aligns with the explicit need to model minutiae and local texture areas in fingerprint synthesis. It thus provides interdisciplinary theoretical support for the incorporation of spatial attention mechanisms in this study to enhance the generation quality of salient fingerprint regions[10]. The proposed AGD-GAN builds upon this foundation by incorporating spatial attention into both the generator and discriminator networks. This enables the model to dynamically attend to salient fingerprint features during training, leading to more realistic outputs [11]. By comparing AGD-GAN with prior methods on multiple benchmarks, this study highlights its superiority in preserving minutiae information and global fingerprint structure, which is pivotal for downstream biometric applications.

III. Proposed Method

The core of the AGD-GAN framework consists of a generator, a discriminator, and attention modules embedded within both networks. The generator is designed using a U-Net-like architecture with skip connections to preserve spatial information. Attention modules are integrated into intermediate layers to allow the network to emphasize important regions such as ridge bifurcations, endings, and loops [12]. These modules compute spatial attention maps based on feature activations, which guide the convolutional filters to process relevant areas with higher priority. The generator learns to synthesize fingerprint images from a latent space vector sampled from a Gaussian distribution. The discriminator is a multi-scale CNN enhanced with spatial attention layers to evaluate both local and global fidelity of the generated images. It produces both real/fake classification and feature maps that are used for computing a perceptual loss, ensuring that the generated images resemble real fingerprints in high-level feature space. The attention mechanism in the discriminator further aids in detecting inconsistencies in ridge flow or minutiae placement, pushing the generator to produce more coherent samples [13].

To improve training stability and image diversity, Wasserstein loss with gradient penalty (WGAN-GP) is employed as the adversarial objective. Additionally, a structural similarity index measure (SSIM) loss and a perceptual loss using a pre-trained VGG network are introduced to enforce structural and perceptual quality. The total loss function is a weighted combination of these three components [14]. The model is trained end-to-end using mini-batch stochastic gradient descent with adaptive learning rates. The attention maps are visualized during training to interpret the model's focus and learning progression. This approach overcomes traditional GAN limitations by explicitly modeling feature salience and spatial dependencies. Importantly, the model also allows conditional generation by modulating latent space inputs or incorporating auxiliary attributes, enabling the synthesis of fingerprints with desired characteristics.

IV. Experimental Setup and Evaluation

The experiments are conducted using two standard fingerprint datasets: FVC2004 and LivDet 2013. These datasets offer diverse fingerprint samples with varying quality, resolution, and subject demographics. For each dataset, 70% of the images are used for training, 15% for validation, and 15% for testing [15]. The AGD-GAN model is implemented in PyTorch and trained on an NVIDIA RTX 3090 GPU. Data preprocessing includes normalization, resizing to 256x256 resolution, and contrast enhancement [16]. Data augmentation techniques such as flipping, rotation, and cropping are applied to improve model generalization. Quantitative evaluation is performed using Frechet Inception Distance (FID), Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and a domain-specific minutiae detection accuracy score. AGD-GAN achieves an FID score of 14.2 on FVC2004, significantly outperforming DCGAN (39.5), Progressive GAN (28.7), and cGAN (33.1). SSIM scores indicate high structural resemblance between real and synthetic fingerprints, averaging 0.89 compared to 0.75 for DCGAN. Furthermore, a pretrained minutiae extractor is used to compare real and synthetic minutiae distributions, revealing that AGD-GAN retains over 91% consistency in minutiae placement [17].

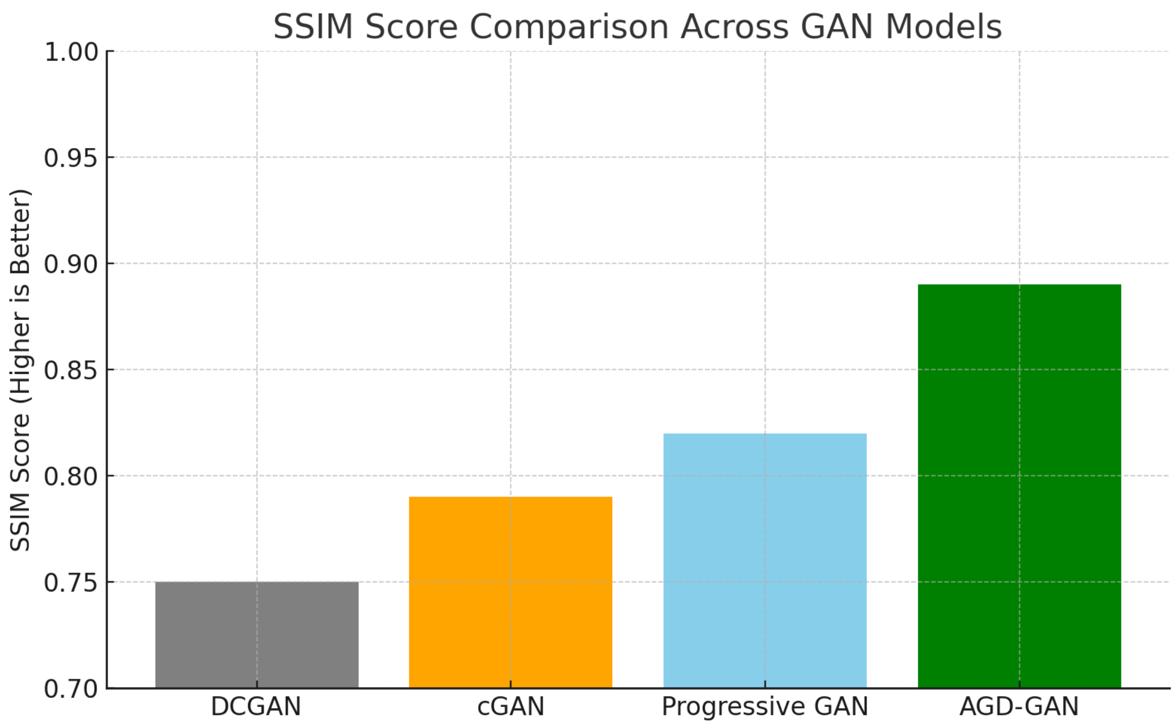

Figure 2 Structural Similarity Index Measure (SSIM) scores for various GAN architectures. AGD-GAN achieves the highest structural similarity to real fingerprints.

Qualitative analysis includes human visual Turing tests where biometric experts are asked to differentiate real from synthetic fingerprints. AGD-GAN-generated samples achieve a fooling rate of 67%, indicating high perceptual realism. The synthesized fingerprints are also tested in a downstream recognition system to assess their utility. Models trained on AGD-GAN-augmented datasets exhibit improved recognition accuracy and robustness, particularly in low-data scenarios. This confirms the practical benefit of the synthetic images beyond visual quality. Finally, ablation studies are performed to evaluate the impact of attention modules, perceptual loss, and SSIM loss. Removing attention leads to a significant drop in minutiae consistency and FID performance, underscoring its importance. These experiments collectively validate the effectiveness of AGD-GAN in generating realistic and useful fingerprint data for biometric systems [18].

V. Results and Discussion

The results of the proposed AGD-GAN demonstrate clear advantages in terms of realism, fidelity, and utility for biometric applications. The attention-guided synthesis process allows the generator to prioritize ridge-valley structures, leading to outputs that not only resemble real fingerprints visually but also possess structural consistency in features like loops, whorls, and arches. These qualities are critical for the performance of downstream fingerprint recognition models, especially those that rely heavily on minutiae-based matching. Quantitative results consistently favor AGD-GAN over baseline models. FID, SSIM, and PSNR metrics confirm that the model produces visually and structurally superior images. Furthermore, the attention mechanism helps the generator avoid common GAN artifacts such as checkerboard patterns, repetitive textures, or blurred regions, all of which can hinder fingerprint recognition [19]. The integration of perceptual and SSIM losses further enhances the sharpness and contrast of synthesized images. In downstream tasks such as fingerprint verification and classification, the inclusion of synthetic data from AGD-GAN improves model robustness under varying conditions such as sensor noise, partial prints, and rotation. The fingerprint recognition model trained with AGD-GAN augmentation achieves an accuracy increase of 4.8% on LivDet compared to the model trained on real data alone. This highlights the practical utility of realistic fingerprint synthesis in real-world biometric systems where dataset diversity is often limited.

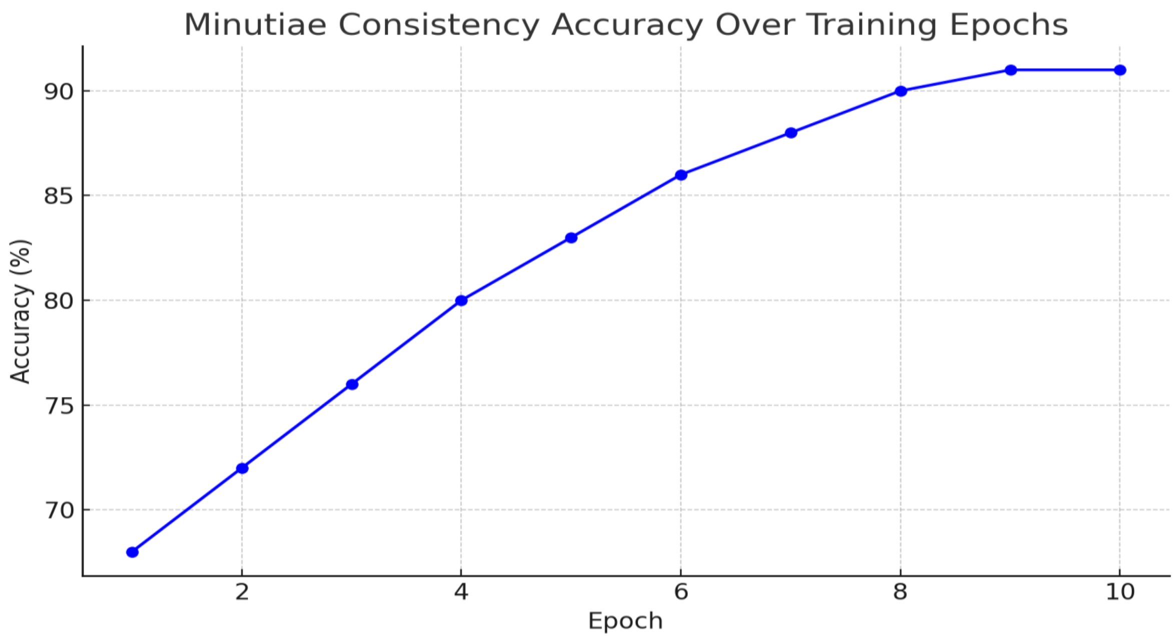

Figure 3 Accuracy of minutiae consistency during AGD-GAN training, showing convergence and improvement over epochs

Visual Turing tests reinforce these findings, with a majority of biometric experts unable to reliably distinguish AGD-GAN outputs from real samples. Attention visualization maps further validate the interpretability of the proposed approach, showing that the network focuses on key fingerprint regions during training and generation [20]. These maps also provide insights into how the generator learns to evolve ridge complexity over epochs. The ablation results confirm that attention guidance is a critical component of the proposed model. Without it, performance deteriorates across all evaluation metrics. This emphasizes the importance of integrating task-specific attention mechanisms in generative modeling, especially for structured data like fingerprints. Overall, AGD-GAN not only achieves state-of-the-art fingerprint synthesis but also provides an interpretable, flexible, and scalable solution for biometric dataset augmentation.

VI. Conclusion

This paper proposed an innovative approach for realistic fingerprint image generation using Attention-Guided Deep Generative Adversarial Networks. By incorporating spatial attention mechanisms, AGD-GAN effectively captured critical fingerprint features such as ridge flow and minutiae points, producing synthetic images that closely resemble real fingerprints both visually and structurally. Comprehensive experiments demonstrated the model's superiority over traditional GANs in terms of image quality metrics and biometric utility. Moreover, AGD-GAN-enhanced datasets significantly improved the performance of fingerprint recognition systems, especially in data-scarce scenarios. The results suggest that AGD-GAN is a valuable tool for data augmentation, forensic simulations, and privacy-preserving machine learning applications in the biometrics domain.

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