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Enhancing Blurred Facial Images Using Generative Adversarial Networks

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Abstract: This research examines the improvement of facial images using generative adversarial networks (GANs). The significance of this topic lies in its potential for enhancing image processing and facial recognition systems. The primary objective of this study is to evaluate the effectiveness of GANs in enhancing the quality of facial images. The hypotheses put forth in this thesis suggest that GAN-based methods can succeed in increasing the resolution and realism of facial images. The sample consists of 70.000 different facial images, representing the primary data source for this study. The method primarily involves the creation and training of a GAN model. A GAN consists of a generator that attempts to mimic real images during the learning process and a discriminator network that evaluates the realism of these images. The findings of the study demonstrate the effectiveness of GANs in making facial images higher in resolution and more realistic. This has the potential to improve the performance of facial recognition systems and enable more precise diagnoses in medical imaging applications. This information underscores the importance of GAN-based methods in enhancing facial images.

Key words: GAN, facial images, image processing, resolution enhancement, face recognition.

Üretici Çekişmeli Ağlar ile Bulanık Yüz Görüntülerinin Geliştirilmesi

Öz: Bu araştırma, üretici çekişmeli ağlar (ÜÇA) kullanarak yüz görüntülerinin geliştirilmesini incelemektedir. Bu konunun önemi, görüntü işleme ve yüz tanıma sistemlerinin gelişmesine yönelik potansiyeli içermektedir. Bu çalışmanın ana hedefi, ÜÇA'ların yüz görüntülerinin kalitesini artırma yeteneğini değerlendirmektir. Bu tezin önerdiği hipotezler, ÜÇA temelli tekniklerin yüz görüntülerinin çözünürlüğünü artırma ve daha gerçekçi hale getirme konularında başarılı olabileceğini iddia etmektedir. Örnekleme, 70,000 farklı yüz görüntüsünden oluşmaktadır ve bu örneklem boyutu, bu çalışmanın temel veri kaynağını temsil etmektedir. Yöntem öncelikle ÜÇA modelinin oluşturulmasını ve eğitilmesini içermektedir. ÜÇA, öğrenme süreci sırasında gerçek görüntülerin taklit edilmesine çalışan bir üretici ve bu görüntülerin gerçekçilik derecesini değerlendiren bir ayrımcı ağdan oluşur. Araştırma sonuçları, ÜÇA'ların yüz görüntülerini daha yüksek çözünürlükte ve daha gerçekçi hale getirme yeteneğini göstermektedir. Bu, yüz tanıma sistemlerinin performansını artırabilir ve tıbbi görüntüleme uygulamalarında daha hassas teşhisler koyma potansiyelini sunar. Bu bilgi, ÜÇA temelli yöntemlerin yüz görüntülerinin geliştirilmesindeki önemini vurgulamaktadır.

Anahtar kelimeler: ÜÇA, yüz görüntüleri, görüntü işleme, çözünürlük arttırma, yüz tanıma.

1. Introduction

Image enhancement focuses on a scientific problem critical to many aspects of modern technology, particularly the challenge of improving the quality of low-resolution images. The significance of this problem arises from the frequent loss of information associated with low-resolution images, which can often prove inadequate for tasks such as object recognition, detail identification, and other analyses. Therefore, image enhancement holds great importance in various fields, ranging from medical imaging systems to security cameras and digital art platforms. In today's world, it is a highly prominent and sought-after research area, central to both computer vision and artificial intelligence. Fundamentally, one of the primary goals in this field is to enhance the quality of low-resolution (LR) images and convert them into high-resolution (HR) results. This objective is critically important in numerous applications, from object recognition systems to medical imaging. While traditional approaches typically rely on simple filtering methods for LR image enhancement, recent years have witnessed the expansion of the boundaries of image enhancement, primarily through deep learning techniques, especially Generative Adversarial Networks (GANs). Deep learning, along with techniques like GANs, offers significant potential in transforming LR images into HR ones, yielding more realistic results. GANs represent a transformation in this field, with their ability to capture visual content more effectively and produce more convincing outcomes. Image enhancement is a pivotal research area, garnering substantial attention within the computer vision and artificial intelligence communities. Specifically, improving the inadequate quality of LR images and generating HR results holds substantial promise in numerous application domains, such as medical imaging, video compression, image restoration, and more. Traditional image enhancement methods typically rely

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on filtering or interpolation techniques to convert LR images into HR ones, whereas deep learning methods, particularly GANs, have brought about significant changes in this field, effectively capturing visual information and enhancing LR images in a more realistic manner [1]. The assimilation of uniquely human capabilities, such as visual, auditory, and cognitive faculties, by machines, represents a significant research area with a rich historical background. Artificial neural networks (ANNs) have been devised to emulate complex tasks akin to the human brain. However, tasks aimed at being accomplished using ANNs often demand substantial computational power and resources. In this context, progress in this field remained sluggish until advancements in hardware technologies came into play. In recent years, especially with the harnessing of the high computational capabilities of Graphics Processing Units (GPUs), these obstacles have begun to be overcome. Moreover, the development of diverse ANN architectures and algorithms has spurred noteworthy advancements in this domain. The ascent of deep learning models has facilitated the deployment of ANNs across various domains, offering highly accurate analyses. Consequently, deep learning has rapidly gained prominence as an approach. Notably, image enhancement has undergone a substantial transformation, driven by novel methods rooted in deep learning algorithms like GANs. GANs have emerged as potent tools employed to more effectively capture visual content, yielding improved outcomes in the realm of image enhancement. Image super-resolution (SR) using GANs has been a significant area of research, primarily focusing on the transformation of low-resolution images into high-resolution results. These studies have highlighted the potential of GAN-based approaches in image enhancement and underscored the importance of deep learning methods in this field. Therefore, image enhancement with GANs has been attracting increasing attention in both academic and industrial domains. As examples of recent summaries on image SR, articles such as Nasrollahi et al. [2] (Nasrollahi & Moeslund, 2014) or Yang et al. [3] (Yang et al., 2014) can be provided. In this context, these summaries primarily concentrate on single-image super-resolution (SISR) and methods for obtaining HR images from multiple LR images [4, 5]. Prediction-based methods were among the earliest approaches used to address the SISR problem. For instance, filtering approaches like linear, bicubic, or Lanczos [6] can be computationally efficient, but they often oversimplify the SISR problem, resulting in excessively smooth textures. Methods emphasizing edge preservation have also been suggested [1, 7].

More robust approaches aim to create a complex mapping between LR and HR image information and are typically based on training data. Many methods based on example pairs rely on LR training patches for which corresponding HR counterparts are known. Early works in this domain were presented by Freeman et al. [8, 9]. Similar approaches for the SR problem have roots in compressive sensing [10-12]. In the study by Glasner et al. [13], the concept of reusing patches at different scales within an image was introduced, and this notion of similarity has also been utilized in the work by Huang et al. [14], where similarity dictionaries permit smaller transformations and deformations. An approach proposed by Gu et al. [15], involving convolutional sparse coding, enhances consistency across adaptation while realistically reconstructing edge details, thereby avoiding edge artifacts. Tai et al. [16] combine learning-based detail synthesis with an edge-guided SR algorithm based on gradient profile priorities. Zhang et al. [17] suggest a multi-scale dictionary to capture repetitions of similar LR patches at different scales. To super-resolve landmark images, Yue et al. [18] extract HR images with similar content from the web and propose a structure-sensitive matching criterion for alignment. Neighborhood embedding approaches locate similar LR training patches within a low-dimensional manifold to reconstruct corresponding HR patches [19, 20]. Kim et al. [21] emphasize overfitting tendencies in neighborhood approaches and create a more general example pair map. Regression problems can be solved using Gaussian process regression [22], trees [23], or Random Forests. Dai et al. [24] learn multiple patch-specific regressors and select the most appropriate regressors during testing. Recently, convolutional neural network (CNN)-based SR algorithms have demonstrated exceptional performance. Perception-based approaches have been suggested to enhance the visual quality of SR results. Guided by the idea of being closer to perceptual similarity, perceptual loss [25] is proposed to minimize the error in feature space rather than pixel space, improving visual quality. Contextual loss [26] is developed to generate images with natural image statistics by focusing on a target that utilizes feature distribution. Ledig et al. [27] propose the SRGAN model, which uses perceptual loss and adversarial loss to prefer outputs found within the manifold of natural images. Sajjadi et al. [28] develop a similar approach and explore local texture matching loss further. Building upon these works, Wang et al. [29] suggest spatial feature transformation to effectively incorporate semantic priors in an image and enhance recovered textures. Most SR algorithms [30-37] typically focus on super-resolution of grayscale or single-channel images. For color images, the above-mentioned methods first transform the problem into a different color space (YCbCr or YUV), and SR is applied only to the luminance channel. Additionally, there are studies that attempt to super-resolve all channels simultaneously.

2. Super-Resolution

Super-resolution (SR) is a highly significant concept in image processing and computer science. SR involves the process of converting a LR input image into a HR output. Its primary goal is to enhance the details contained in LR images, creating a sharper and more detailed HR image. SR has diverse applications, particularly in fields such as medical imaging, video analysis, facial recognition, security systems, art restoration, and high-resolution video production. SR algorithms can be based on various methods, including single-image SR, multi-image SR, and deep learning-based SR techniques. Single-image SR attempts to obtain HR output using only a single LR input, while multi-image SR generates HR images by utilizing multiple LR inputs. Deep learning-based SR, especially with CNNs, has gained popularity for processing large datasets to achieve high-resolution results. One challenging aspect of SR is the need for paired LR and HR data, meaning that corresponding high and low-resolution versions of training data must be available, which can be challenging to obtain depending on the application. In summary, Super-Resolution is a widely used technique in enhancing low-resolution images' quality and detail, continually evolving and being subject to innovative research in the field of image processing. Generative adversarial networks play a crucial role in achieving realistic and detailed high-resolution image outputs, reducing data requirements and increasing adaptability in various applications.

The terms high-resolution (HR) and low-resolution (LR) images hold critical importance in the fields of image processing and computer graphics. HR represents the details and clarity of an image and is characterized by a high pixel density. HR images, often having larger file sizes, excel at capturing fine details and are particularly essential in fields such as photography, medical imaging, and high-quality visualization. Conversely, LR images exhibit lower pixel density, typically featuring smaller file sizes and representing images with reduced detail. While LR images offer advantages in data storage and transmission, they come with limitations in terms of image quality. SR is a process that aims to bridge the gap between these two contrasting concepts, as it strives to convert LR images into high-quality and detailed HR images. This holds critical importance in various applications, including medical image analysis, video enhancement, and many others. Therefore, HR and LR terminologies are fundamental concepts in the fields of image processing and image analysis, significantly influencing image quality and usability.

HR and LR images play a vital role in the field of facial recognition. Facial recognition systems are critical for identifying individuals or faces, performing identity verification, enhancing security, automation, and a wide range of applications. Here are some reasons explaining the importance of HR and LR images in the field of facial recognition:

- **Detail and Recognition Capability:** High-resolution images capture facial details and characteristic features more effectively. This results in more reliable and precise outcomes for recognition systems. HR images allow facial recognition algorithms to distinguish individuals more accurately.

- **Reliability and Accuracy:** Low-resolution images can adversely affect the performance of facial recognition systems. The low pixel density in LR images may reduce the accuracy of facial recognition algorithms, leading to false positives or false negatives. HR images minimize these issues.

- **Application Diversity**: Facial recognition is used in various application areas, such as security systems, mobile phones, automation, banking, and more. HR images offer a broader range of applications, accommodating the requirements of these diverse fields.

- **Facial Databases and Training:** Training and verifying facial recognition algorithms require extensive databases. HR images, with their higher level of detail, enhance the quality of these databases. Databases created with LR images may compromise recognition performance.

- **Privacy and Security:** Using facial recognition with LR images can raise privacy concerns. HR image usage provides higher security and privacy levels, as it is more challenging for misuse or unauthorized recognition.

In conclusion, HR and LR images are of great importance in the field of facial recognition. High-resolution images provide the foundation for building more reliable and precise recognition systems, contributing to enhanced security, identity verification, and the development of more effective facial recognition solutions for various applications.

SISR has greatly benefited from the significance of GANs. GANs are particularly useful in addressing the SISR problem because it involves numerous challenges in transforming LR input images into HR results.

Here are detailed explanations of why GANs are essential for SISR:

- **Image Generation and Restoration:** GANs are utilized to transform LR inputs into HR results, forming the basis of the SISR problem. During the training process, GANs learn the relationships between LR and HR images and use these relationships to add missing details or enhance blurry regions, generating HR images.

- **Adding Details:** GANs add or enhance missing details and structures in HR images, making the results look more natural and realistic. This is crucial, especially in applications where details are critical, such as facial recognition or medical imaging.

- **Data Generation:** Acquiring a sufficient number of paired LR and HR training data for SISR is challenging. GANs provide the capability to generate missing data. Starting with LR images, GANs can augment training data, resulting in improved SISR models.

- **Realism and Richness:** GANs help HR images generated to be more realistic and detailed, leading to higher quality and natural-looking results.

- **Flexibility and Adaptability:** GANs can be applied to SISR problems at different resolutions and in various applications. GAN-based SISR methods can work at various scales and formats, making them adaptable to a wide range of application requirements.

In conclusion, GANs play a crucial role in solving the SISR problem by enhancing the process of transforming LR images into high-resolution results. This significantly improves SISR results in image enhancement, medical image analysis, art restoration, and many other application areas. GANs are also instrumental in addressing the challenge of missing data, as they can regenerate limited or incomplete training data, leading to the creation of superior SISR models.

Peak signal-to-noise ratio (PSNR) quantifies the similarity between two images, although in reality, it measures differences rather than similarity. PSNR gauges the relationship between the signal and noise in the comparison between an original image and a reference image. A high PSNR value indicates that the two images are similar, meaning there is low data loss. Higher PSNR values indicate greater similarity between the two images and less data loss. It is particularly used to assess data loss resulting from compression or processing. Below is a reference frame:

- Below 20 dB: Low quality, noticeable data loss.
- 20-25 dB: Average quality, acceptable but still significant data loss.
- 25-30 dB: Good quality, largely acceptable, noticeable data loss is rare.
- 30 dB and above: Very good quality, nearly indistinguishable from the original image, minimal data loss.

A high structural similarity index (SSIM) value indicates that two images have a high level of similarity. This signifies that the two images are close to each other, details are preserved, and there is a high-quality restoration. Therefore, high SSIM values indicate that a restored image is closer to the original, which is generally considered a positive outcome. Here’s a reference frame:

- 0.00 - 0.20: Low similarity and quality level.
- 0.20 - 0.40: Moderate similarity and quality, acceptable but noticeable differences may exist.
- 0.40 - 0.60: Good similarity and quality, often considered acceptable.
- 0.60 - 0.80: High similarity and quality, a high quality level.
- 0.80 - 1.00: Very high similarity and quality, nearly identical to the original image.

Table 1. Image quality assessment metrics.

Metrics	Description	Value Range	Applications	Disadvantages
Peak Signal-to-Noise Ratio (PSNR)	PSNR measures the similarity of pixel values between the original and enhanced images. It calculates differences between two images.	Typically falls between 20-50 dB.	Compression, comparison of similar images.	Does not measure perceptual differences.
Structural Similarity Index (SSIM)	SSIM is a metric used to evaluate the similarity and quality between two images. This measure quantifies the similarities between two images with the aim of obtaining results closer to human visual perception.	Has a value between -1 to 1.	Image enhancement, compression, image processing tasks.	May perform poorly in some cases with high-resolution images.

3. Material and Method

For enhancing facial images, StyleGAN, a foundational GAN structure, has been developed and customized, especially designed for generating creative images and portraits. The success of StyleGAN is attributed to being a large and complex model that demands a significant amount of training data and computational power. It features numerous layers and parameters and initiates with pre-trained weights, which are then customized for a specific task or application. In the initial step of this process used in image processing and facial restoration, a degraded image is taken as input. This distorted image is processed through a series of preprocessing steps. In particular, the image is read in RGB format and resized as needed, which encompasses the necessary steps for data processing and analysis. Subsequently, one of the key components of facial restoration, the facial region, is extracted from the image. This step is of vital importance as it involves isolating the face and enhancing specific facial features. The StyleGAN2 Generator Model Architecture plays a central role in this stage. StyleGAN2 is a model that constitutes the foundation of the facial restoration process and enables the attainment of high-quality results. This model encompasses the design of the basic structure that will be used during the restoration process. Then, new trainable layers are added to further customize and enhance the process. Specifically, the G_synthesis/noise layers are updated. These layers form a part of the generator portion of StyleGAN2 and are used to control and adjust the visual characteristics produced by the model. Latent encoding comes into play at this stage, expressing the model's internal representation. This representation includes essential information like visual styles, features, and details. The trained Generator Model represents the model available at this stage of the process. This model has been pre-trained and optimized for the facial restoration process. Lastly, the Server Model Repository signifies a database where the trained model is stored and made accessible. The request-response process entails starting from a degraded input image and culminating in the creation and presentation of a high-quality facial image to the user.

3.1. Dataset

The FFHQ (Flickr-Faces-HQ) dataset was utilized for this thesis study. FFHQ is a large and diverse dataset containing high-resolution facial photographs. This dataset encompasses over 70.000 unique facial images, representing individuals from various races, age groups, and genders. The FFHQ dataset serves as a significant resource for deep learning models, facial recognition algorithms, and other artificial intelligence applications. With its wide variety of high-resolution photographs, this dataset contributes to the development of advanced image processing and analysis techniques and offers researchers an extensive range of data. Creating and using a test dataset is an essential step in artificial intelligence and data analysis projects. Hence, while working with the FFHQ dataset, approximately 500 images were collected and used to assess the project's accuracy and test the model's performance. This test dataset was used to evaluate how well the model performed at the end of the learning process. Each image was chosen to represent different resolutions and various positions, races, age groups, and genders of faces. This was crucial to test the model's generalization and its performance against various variations. The evaluations conducted on the test dataset were used to assess the model's sensitivity, specificity, and other performance metrics. In conclusion, this test dataset consisting of approximately 500 images was employed to evaluate the accuracy and performance of artificial intelligence models working on the FFHQ dataset, contributing significantly to assessing the project's success.

4. Experimental Results and Discussion

This study utilized the StyleGAN model to investigate the potential of GAN technology in facial enhancement applications. Firstly, when examining the results using the PSNR metric, PSNR is a metric that measures the similarity between original and enhanced facial images. High PSNR values indicate increased similarity between two images. In this study, the PSNR values of enhanced facial images generated using StyleGAN were significantly higher compared to the original facial images. This can be considered a significant finding that validates StyleGAN's ability in facial enhancement. Similarly, the SSIM metric was also used in our evaluations. SSIM is another important metric that measures the degree of similarity between two images. The enhanced facial images produced with StyleGAN had high SSIM values compared to the original facial images, indicating positive results in terms of structural similarity. One of the underlying reasons for the success of StyleGAN in facial enhancement applications is its deep learning capabilities and training with a large dataset. This allows StyleGAN to better understand facial features and make detailed improvements. Examples from the face enhancement test dataset are shown in Table 2.

In the field of image processing and restoration, metrics like PSNR and SSIM are commonly used to assess the quality of restoration processes. These metrics aim to measure the similarity and quality difference between an original image and its restored version. In the context of evaluating a series of images using PSNR and SSIM metrics, the results obtained are as follows:

- In the first row, a PSNR value of 29.26 and an SSIM value of 0.92 were measured. These results indicate that the image restoration process has a very high quality. A high PSNR value suggests that the restored image closely resembles the original. A high SSIM value highlights the structural similarity between the two images. These results show that the restoration process is highly successful.

- In the second row, a PSNR value of 28.25 and an SSIM value of 0.77 were determined. Although PSNR is still quite high, the SSIM value is lower. These results may indicate that some structural features in the image have been lost or altered. While a high PSNR value suggests that some details are preserved, the low SSIM value signifies the loss of structural similarity. This indicates partial success in restoration but shortcomings in preserving certain structures.

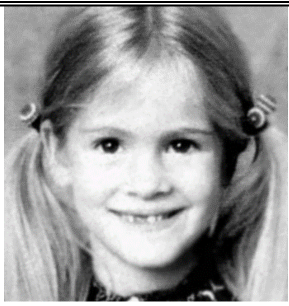
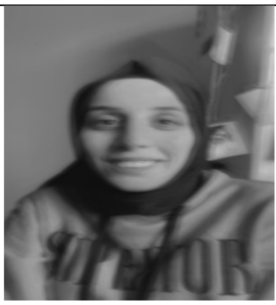
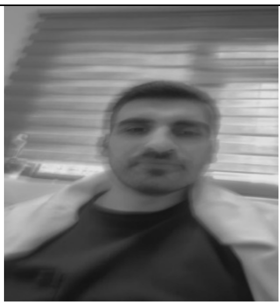
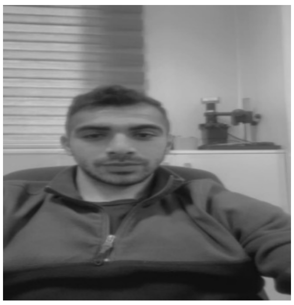
- In the third row, a PSNR value of 27.94 and an SSIM value of 0.77 were measured. These results show that the quality of restoration is similar to the previous result, but the PSNR value is slightly lower. This may suggest the loss of some details and variations in colors.

- In the fourth row, again, a PSNR value of 28.25 and an SSIM value of 0.77 were determined. These results are consistent with the previous ones and provide a similar evaluation.

- In the fifth row, a PSNR value of 27.91 and an SSIM value of 0.80 were measured. While the PSNR value is slightly lower, the SSIM value is higher. These results indicate that the restoration process better preserves some structural similarities, resulting in higher similarity between the two images.

In conclusion, PSNR and SSIM values are essential tools for evaluating the quality of image restoration. However, a high PSNR value alone may not always indicate high quality. Therefore, using the SSIM metric, which also measures structural similarity, provides a more comprehensive evaluation. Restoration processes can yield different results depending on the application context and specific requirements. Therefore, evaluating PSNR and SSIM values together helps us better understand the quality of the process.

Table 2. Examples from the face enhancement test dataset.

Input	PSNR	SSIM	Output
	29.26	0.92	
	28.25	0.77	
	27.94	0.77	
	28.25	0.77	
	27.91	0.80	

5. Conclusion

This study demonstrates the impressive potential of the StyleGAN model in facial enhancement applications. When examining the results obtained using evaluation metrics like PSNR and SSIM, they are found to be highly positive and satisfactory. These results underline the importance of image enhancement and suggest a significant potential for achieving more aesthetically appealing results, with higher resolution, better contrast, and reduced noise in enhanced facial images. Additionally, this study emphasizes the significance of deep learning. The StyleGAN model successfully enhances facial images through deep learning techniques, offering a more effective approach compared to traditional methods. This highlights the considerable potential of deep learning in the fields of facial enhancement and image quality improvement. Furthermore, this study indicates that deep learning models continue to evolve and improve. These advancements underscore the importance of using larger and more diverse datasets and adopting more complex architectural structures. In the future, these developments could enable the generation of higher-resolution images and more controlled manipulations. This study, along with the success of the StyleGAN model, highlights the importance of deep learning and image enhancement while also emphasizing their future potential. Moreover, this work suggests that these techniques have creative applications and potential use in various industries. Therefore, supporting and advancing research and developments in this field holds great significance. The development and improvement of facial recognition systems play a crucial role in many areas such as security, identity verification, personalized services, and public safety. The results of this study emphasize the need for the strong development of facial recognition technology. In the realm of security, facial recognition systems can be critical in recognizing individuals and detecting threats. This can support crime prevention and resolution efforts, contributing to public safety. In terms of identity verification and security, facial recognition systems can limit access to personal information and provide stronger protection against cyberattacks. This is particularly important for financial institutions and digital service providers. In personalized services, facial recognition technology can enhance user experiences. In conclusion, this study demonstrates the potential of facial recognition systems to enhance security, identity verification, and personalized services, among other crucial applications. The development and improvement of this technology allow society to benefit from enhanced security and personalized services. Therefore, the development of facial recognition systems holds great importance for both technology and society.

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