Facial Image Restoration Using GAN Deep Learning Model

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Abstract - *Facial image priors, such as the facial geometry prior or the facial reference prior, are required for facial image restoration. These are utilized to restore details and naturalness of facial feature. The extremely poor and significantly damaged inputs are unable to provide precise geometric prior. And it's difficult to find references of good quality. The facial prior's application in practical situations is constrained by these factors. The GAN is performing tremendously better in image generation. Therefore, this GAN may restore facial images by leveraging rich and diversified priors. The GAN is utilized during the process of restoring the face, because of its complex design as well as power use of generative facial prior. This GAN could perform both restore facial details as well as enhance quality and colors. This GAN may achieve superior performance on both real-world and synthetic datasets. Now a days more attention is taken by image generation. Many industrial applications looking for facial and text image restoration without losing its identity, that is the important thing to achieve. Generative adversarial networks are excellent in image editing and has the great potential to produce natural images.*

Key Words: **Image Restoration, Image Processing, GAN Model, Neural Networks, Deep learning**

1. INTRODUCTION

Facial image restoration has the goal of recovering the high-quality images from the low-quality images. These low-quality images may have the degradation, which is consist of low resolution, noise, blurriness etc. It is very difficult to recover these images due to severe degradation, variety of poses, and different expressions. The work happened till now took the approach of using face specific priors to restore the facial image. These priors used to create the face shape and feature details. Another approach of using the of using the facial component dictionary. Which is used to generate the more realistic and natural images.

So, here the deep learning method can leverage the capability of GAN that generates the facial images. This can generate more natural faithful faces with different variety. This creates the diverse and rich geometry priors, with variety of texture and colours. This enables the recovery of facial characteristics, and the improvement of colours Use the generative priors for real-world face restoration using pertained face Generative Adversarial Network (GAN) model. Previous attempts visually give the natural, soft outputs, but low accuracy images are produced as output. These methods not good at accurate restoration guidance.

To overcome these issues, the proposed GAN method may achieve more natural and accurate images. The degradation removal and facial features restoration are the important steps, which impacts the performance of the process.

2. LITERATURE REVIEW

CNN models achieved great success in facial image restoration. It performs de-blurring, improving the resolution and many other face processing jobs with high accuracy. CNN analysis the images with its layers.

In order to rebuild the high-resolution output from a very low-resolution facial image, Huang et al. suggested a CNN model that uses wavelet coefficients[1]. For recovering the photos, Cao et al. recommended a reinforcement learning technique[2]. The face hallucination approach uses a recurrent policy network to specify the subsequent attended region. The local enhancement network is then used to recover it. In order to reduce face image blurring,

Chrysos et al. devised a technique that takes advantage of the well documented structure, description, and details of face[3]. And Xu et al. came up with a generative adversarial network for de-blurring of face and text[4]. The global semantic face priors can be used to restore the shape and details of face images. This technique is explored by Shen et al[5]. So, these are the existing single image restoration methods. The cons with these are, they perform poorly to real-world low quality, degraded face images. Also, they perform not so good due to the different poses and variety of severe degradations.

In some CNN approach images are enhanced by transferring intensity images' structural details. One is guidance and another is degraded image, both are used in the face restoration process. According to Zhang et al. used a lengthy and difficult searching method by using a reference image with similar content[6]. In the space of features, it is applied to map high resolution image as a guidance with a low-resolution deteriorated patch.

Facial image restoration may be done using the predefined three-dimensional parameterized models or CNN, which is used to represent the face. This method has the capability to describe the faces, different poses, and deviated head positions. But this method is unable to describe the complex expressions and facial postures.

Reference priors uses the reference image of same identity. To overcome this in DFDNet[7] each face component dictionary like eyes, mouth constructed with CNN features. This dictionary is used to restore the facial image[8]. Here, DFDNet primarily concentrates on elements found in the dictionary, and as a result, performance deteriorates in the area outside the dictionary's coverage.

3. PROBLEM STATEMENT

Given an input degraded low-quality facial image x, the aim of face restoration is to generate a high-quality image that is as real and accurate as the original image y. The goal of facial image restoration is to produce a high-quality image that is as comparable to the original image y in terms of realness and accuracy, given an input facial image x that has undergone degradation.

To do this the features are divided, enhanced, and restored with superior information preservation mechanisms, So, this GAN model will have the advantages over the old one. So, that facial image restoration can be done with sufficient information of facial textures and details. This helps to achieve accurate and correct texture high quality images.

The objectives are –

1) Remove degradation
2) Enhance facial details
3) Retain face identity

4. EXISTING SYTSEM

Image restoration means super resolution, de noising, de blurring etc. To achieve visually good results, the solution is pushed closer to the natural manifold. With two usual face-specific priors, face restoration is performed.

First one is Geometry priors, it includes facial components like facial landmarks, face parsing maps, and facial component heat map. These rely on estimations generated using inferior-quality data and worsen when applied to actual situations. They may not include enough information for restoration because they primarily concentrate on geometry considerations.

Second one is Reference priors. It generally uses reference pictures of the same person. This gets degrade in the region beyond its dictionary scope.

The work happened till now was using the geometric priors or the reference priors specific to facial features. The correct recovery of the face's shape and its details benefits from the application of geometric priors. While reference priors are helpful for creating realistic images. These methods perform not good at very low-quality inputs and has limited information about texture and facial details.

5. PROPOSED SYSTEM

To overcome the limitations of existing work the deep learning GAN[9] model can be used. Which may achieve the better results. The deep learning method can leverage the capability of GAN to produce the generative facial priors[10]. The geometric values from the degraded images have adequate information, so those are not considered here. This method treats the whole face image to restore, so that identity is maintained. To achieve this in proposed model the existing model is modified.

The main modules are –

1) Degradation removal module
2) Facial image restoration module

5.1 System Architecture

The Architecture consists of model training and consumption module. Data of different human faces is collected from the different data sources for example FFHQ (Flicker Faces High Quality images). The images are degraded, and supervised dataset is prepared consisting of degraded and clear image.

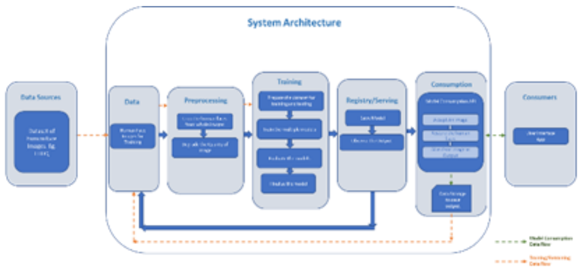

Fig -5.1: System Architecture

The model is trained using the prepared dataset. The models are trained multiple times and better model is finalized. The trained model is saved. And it is consumed for the restoring the images by giving the input

5.2 Model Architecture

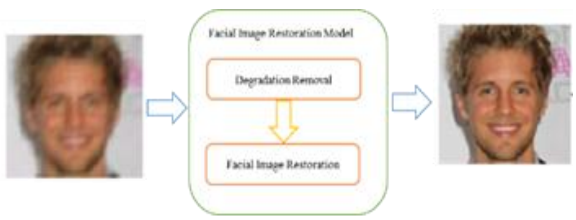

Fig -5.2: Model Architecture

The Architecture consists of two important steps, one is of removing the degradation and then restoring the image with facial feature details. These two modules are inter-connected with the technique of latent code mapping. Specifically, the degradation removal module removes the complicated degradation from the input image. And extract latent features are converted into latent code which are used to map closely with the input image. Facial image restoration module takes the closest latent code mapped with input image and then generate the corresponding output.

6. IMPLEMENTATION

While training the model train with the original image and with the degrade image. So, the model will learn how the image can restored. At the front end the user can upload the image as input to the system. The image is passed to the model. The model will process the image and restores it. The generated new image is given to the user as output.

To implement the proposed model, the solution involves the following steps –

1) Data Gathering:

To train the model the data is collected from the different data sources for example FFHQ (Flicker Faces High Quality images)., it uses 10,000 photos of excellent quality. Each image has been downsized to 512 × 512 pixels. Model training is done using this dataset. To evaluate the created model the four test datasets are gathered, those are CelebA-Test, LFW-Test[11], CelebChild-Test and WebPhoto-Test. These datasets are all distinct from the training examples. The dataset is consisting with variety of facial images having different age group, skin colour, style, pose and gender.

2) Training The Model:

From the collected dataset, prepare the training dataset and train the model. Save the trained model.

3) Evaluate The Model:

Evaluate the created model using the test dataset and observe the output. To evaluate the model FID, NIQE, PSNR and SSIM. The model is good at FID and NIQE, but not good at PSNR and SSIM.

4) Sample Input-Output:

Example 1 – Gray scale image as input

Fig -6.1: Input image at left, and restored output image at right

Example 2 – Colour image as input

Fig -6.2: Input image at left, and restored output image at right

7. APPLICATION

Facial image restoration has a wide range of applications. The old photos can be converted into a brand-new photo. Many applications require the high-quality images as input. In that case the image restoration acts as a pre-processing step. The blurriness can be removed, and photo can be made clear. While taking the photo if the camara is mis-focused, the photo can be restored easily using this model.

8. LIMITATION

The model performs well on most of the faces. But there are limitations found while restoring some images. When the degradation of input image is severe the output image looks artificial. The model produces unnatural images for some images. The model is trained on facial images, so only facial image restoration can be done. The model may not produce the images with full identity.

9. FUTURE WORK

This method may produce the unnatural images for very large poses or generated image may look like artificial. This is because we are using the synthesized data to train the model. In the next step the model can be created with real data. Which may improve the performance. Here, the model can restore the facial images. So, in the next step the model can be trained for text and other things restoration.

10. CONCLUSIONS

The deep learning method that leverages the capability of GAN to generative facial priors for the facial restoration. This allows to achieve the good realness and accurate images. Achieve the super capability to restore the images, improve the resolution with colour enhancement.

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