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Facial Blind Image Restoration Using Deep Learning

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***ABSTRACT*:-**

Face image restoration usually relies on facial priors, such as facial geometry prior or reference prior, to restore realistic and faithful details. However, very low-quality inputs cannot offer accurate geometric prior while high quality references are inaccessible, limiting the applicability in real-world scenarios. In this work, propose the modification of the GAN that leverages rich and diverse priors encapsulated in a pre trained face GAN for face restoration. This new GAN is incorporated into the face restoration process via spatial feature transform layers. Because of the powerful generative facial prior and delicate designs, this new GAN could jointly restore facial details and enhance colors with just a single forward pass, while GAN inversion methods require image-specific optimization at inference. With this new GAN we may achieve superior performance on both synthetic and real-world datasets.

Image generation has attracted broad attention in recent years. Within these works, synthesizing a face from different angles while retaining identity is an important task, because of its wide range of industrial applications, such as video monitoring and face analysis. Recently, this task has been greatly advanced by a number of models of Generative Adversarial Networks. To tackle the task of face reconstruction, existing approaches typically apply predefined parameterized 3D models or Convolution Neural Network (CNN) to represent face. Despite exhibiting promising ability in describing faces, different head poses positioning has obvious deviation. In addition, the methods cannot describe complex expressions and facial postures. , Therefore, complex parametric fitting requires lots of precise data and detailed descriptions. Generative adversarial networks have recently demonstrated excellence in image editing which shows great potential in producing realistic images.

Keywords—: Image Processing, Deep Neural Networks

I. INTRODUCTION

Face image restoration aims at recovering high quality faces from the low-quality images suffering from unknown degradation such as low resolution, noise, blurriness etc. In real time scenarios, it becomes more challenging, due to more complicated degradation, diverse poses, and expressions.

Now, we will leverage the pertained face generative adversarial network model that is Style GAN. These can generate faithful faces with a high degree of variability, which provides rich and diverse priors such as geometry, facial textures, and colors, making it possible to restore facial details and enhance colors. It is challenging to incorporate generative priors into the restoration process. Previous attempts visually give the realistic outputs, but they usually produce images with low accuracy. These are insufficient to guide accurate restoration.

To address these challenges, we propose modified GAN to achieve a good balance of realness and accuracy in a single forward pass. Specifically, modified GAN consists of degradation removal module and pertained face GAN. Besides, have the facial component loss with local discriminators to further enhance facial details, to improve accuracy.

In this paper our approach is to use the Generative Facial Prior (GFP) for real-world blind face restoration, i.e., the prior implicitly encapsulated in pertained face Generative Adversarial Network (GAN) models such as Style GAN. These face GANs are capable of generating faithful faces with a high degree of variability, and thereby providing rich and diverse priors such as geometry, facial textures and colors, making it possible to jointly restore facial details and enhance colors. However, it is challenging to incorporate such generative priors into the restoration process. Previous attempts typically use GAN inversion. They first 'invert' the degraded image back to a latent code of the pertained GAN, and then conduct expensive image specific optimization to reconstruct images. Despite visually realistic outputs, they usually produce images with low fidelity, as the low dimension latent codes are insufficient to guide accurate restoration

II. LITERATURE REVIEW

Recent years have witnessed the unprecedented success of deep CNNs in several face image restoration tasks, e.g., de blurring and super-resolution. In terms of face hallucination.

Huang et al. proposed a wavelet-based CNN model that predicts the wavelet coefficients for reconstructing the high-resolution results from a very low resolution face image. Cao et al. suggested a reinforcement learning based face hallucination method by specifying the next attended region via recurrent policy network and then recovering it via local enhancement network.

As for blind face de blurring, Chrysos et al. developed a domain-specific method by exploiting the well-documented face structure. Xu et al. presented a generative adversarial network (GAN) for face and text de blurring. Shen et al. incorporated the global semantic face priors for 2707 better restoring the shape and details of face images. In general, existing single image restoration methods generalize poorly to real-world LQ face images due to the intrinsic posedness and variety of unknown degradations. In contrast to single image restoration, the introduction of exemplar image can largely ameliorate the difficulty of image restoration and usually results in notable performance improvement. In guided depth image enhancement, the color guidance image is assumed to be spatially aligned with the degraded depth image. And several CNN methods have been suggested to transfer structural details from intensity image to enhance depth images. However, as for blind face restoration, the guidance and degraded images are usually of different poses. Using a reference image with similar content, Zhang et al. adopted a time- and memory-consuming searching scheme to align high-resolution guidance and low-resolution degraded patches in the feature space.

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Problem Statement

The problem statements we've got are having strong and automated face detection, analysis of the captured image and its meaningful analysis by facial expressions, creating data sets for taking a look at and coaching and so the planning and therefore the implementation of utterly fitted classifiers to be told underlying classifiers to be told the vectors of the facial descriptors.

We propose a model design that is capable of recognizing up to six models that are thought-about universal among all walks of cultures. The main are concern, happiness, sadness, surprise, disgust, and in conclusion surprise.

Existing System

Image restoration typically includes super resolution, noising, de blurring etc. To achieve visually good results, solution is pushed closer to the natural manifold. Face restoration is done with two typical face specific priors. Geometry priors include facial components like facial landmarks, face parsing maps, and facial component heat map. These require estimation from low quality inputs and gets degrade in real world scenario. They mainly focus on geometry constraints and may not contain adequate details for restoration.

Reference priors usually rely on reference images of the same identity. This gets degrade in the region beyond its dictionary scope.

The previous work typically exploits face-specific priors in face restoration, such as facial landmarks, parsing maps, facial component heat maps, and show that those geometry facial priors are important to recover accurate face shape and details. However, these are usually estimated from input images and gets degrade with very low-quality inputs. In addition, these contain limited texture information for restoring facial details.

II. *PROPOSED SYSTEM*

Given an input facial image x suffering with degradation, the aim of face restoration is to estimate a high-quality image ŷ which is as similar as possible original image y in terms of realness and accuracy. To achieve this in proposed model the existing model is modified. The main modules are –

1) Degradation removal module
2) Facial feature recognizer
3) Channel Split Spatial Feature Transform

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

1) Data Gathering:

To train and evaluate the model train and test dataset need to be prepared. To train the model we use FFHQ dataset, which consists of 70,000 high quality images. These all images resize to 512 X 512 pixel. Train the model using this data to generalize to real world images during inference. To evaluate the created model the test dataset is prepared. All these datasets have no overlap with training dataset. Both the dataset has different age group, skin colour, style, pose and gender.

2) Training The Model:

From the collected data prepare the training dataset and train the model with small batches for n number of iterations. Save the final best model.

3) Testing The Model:

Evaluate the created model using the test dataset and observe the output. Accordingly decide on next steps.

4) Consuming The Model:

To consume the saved model, create an API. This API can be used to give the input and get the output from the model.

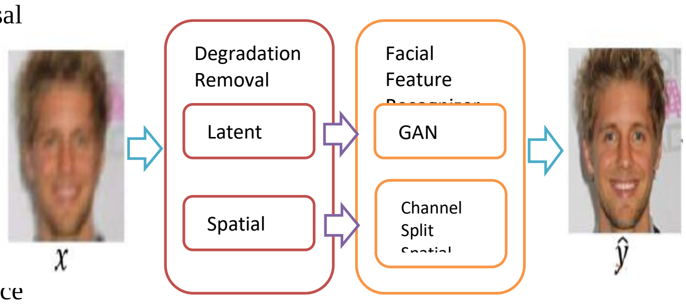

Fig1. System Architecture

The Architecture consists of a degradation removal module and a pretrained GAN (such as StyleGAN2) as a facial feature recognizer. They both are inter-connected by a latent code mapping technique and several Channel-Split Spatial Feature Transform (CS-SFT) layers. Specifically, the degradation removal module is designed to remove the complicated degradation in the input image and extract two kinds of features:

1) latent features to map the input image to the closest latent code in StyleGAN2
2) spatial features for modulating the StyleGAN2 features

During the model training, it emphasizes the following:

1) Intermediate restoration losses to remove complex degradation
2) Facial component loss with discriminators to enhance facial details.
3) Identity preserving loss to retain face identity.

III. RESULTS

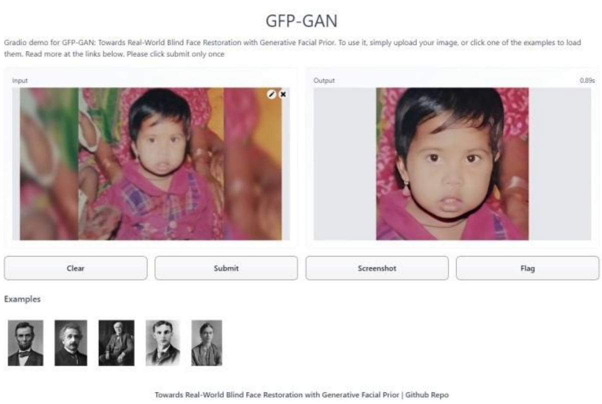

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Fig2. Result of Face

The Fig2 Shows the Result of face. After applying the processing the resulting image will get improve.

IV. CONCLUSION

The paper presents GFP-GAN framework for the facial prior detection of blind face restoration. We have proposed the GFP-GAN framework that leverages the rich and diverse generative facial prior for the challenging blind face restoration task. This prior is incorporated into the restoration process with channel-split spatial feature transform layers, allowing us to achieve a good balance of realness and fidelity. Extensive comparisons demonstrate the superior capability of GFP-GAN in joint face restoration and color enhancement for real-world images, outperforming prior art

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