

LOW RESOLUTION FACE RECOGNITION

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Abstract--- This paper presents the conversion of low resolution images into high resolution by using a several techniques. A Facial Recognition system is a technology capable of identifying or verifying a person from a digital image or a video frame. Face recognition Super-Resolution (SR) methods can be employed to enhance the resolution of the images. Face Re-identification (RE-ID) is done by several Deep Learning based approaches and improved by introducing Generative Adversarial Network. The performance of super-resolution augmented face recognition techniques employing LR face inputs from two popular face datasets (AR and YouTube Faces).

Index Terms— Super Resolution, Face Recognition, Face REID, GAN, Datasets.

I. INTRODUCTION

In recent years, we have witnessed tremendous improvements in face recognition system performance, especially when employing different specially designed deep learning architectures. these algorithms can deal effectively with faces with significant pose

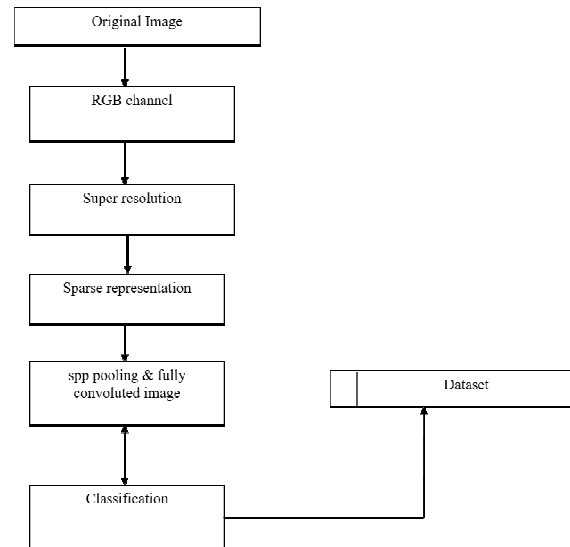
variations, these faces generally need to be large in area. Also, pre-processing techniques such as face frontalization and face alignment are needed. HR face image data, cannot be applied directly to low-quality face images. Practical face recognition systems for images captured in surveillance scenarios can address face identification tasks (using a watch list) and face re-identification tasks (where a

subject is matched to a previous appearance in a surveillance system). We address the LR face recognition task in a larger scope which includes a qualitative exploration of the recognition performance gap between controlled facial images and video quality face images using super-resolution techniques, face identification, and face re-identification.

II. LOW-RESOLUTION FACE-ID

We first focus on face identification which applies when the enrolled face images are mostly collected in controlled scenarios with HR and LR faces are captured with surveillance cameras with an uncontrolled pose and lighting conditions. This is a challenging recognition task which relies strongly on a good resolution invariant representation.

III. DATA-FLOW DIAGRAM



IV. SUPER RESOLUTION

In order to explore the gap between the constrained and unconstrained LR face recognition performance, we designed a small super-resolution (SR) experiment. with the AR datasets. In this experiment, the idea is to evaluate the matching performance of two face images: a LR image and a HR image. Most of the LR face images used for research are generated by down sampling a standard face recognition dataset that is collected in a controlled environment. We select the AR dataset to research the LRFR task under uncontrolled scenarios and other

unconstrained LR face datasets for more exploration.

RGB CHANNEL

After the data set collection the original image is converted into red down sampling channel and green down sampling channel and blue down sampling channel.

SPARSE REPRESENTATION

Images are sparse if it can have very few non-zero coefficients re-presentation in certain sub-space. Sparse is good classification because It Separate samples from different classes. Only when data points are intert-wined classification is hard.

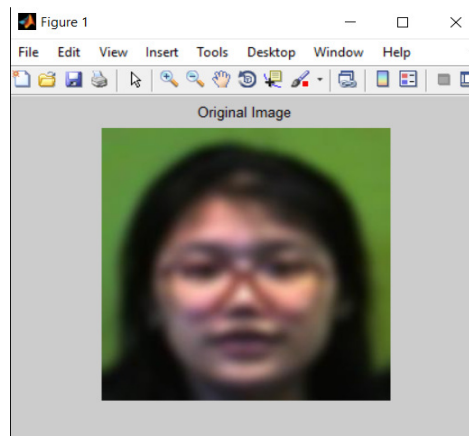


FIG 1. ORIGINAL IMAGE

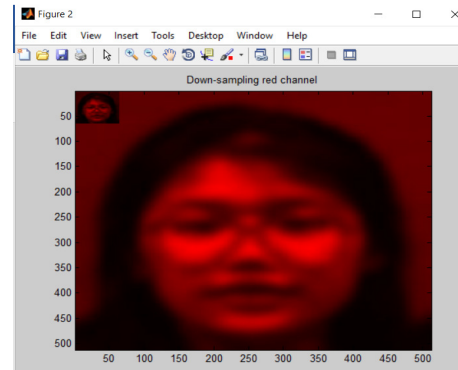


FIG 2. DOWN SAMPLING RED CHANNEL

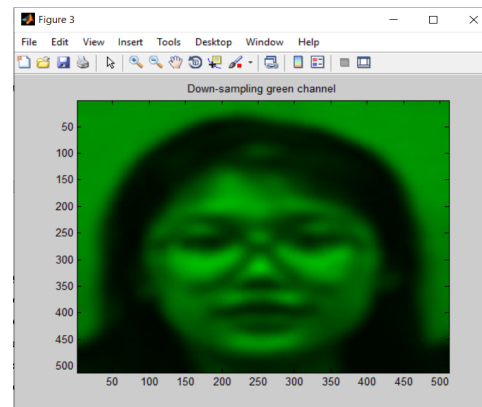


FIG3.DOWNSAMPLINGGREEN CHANNEL

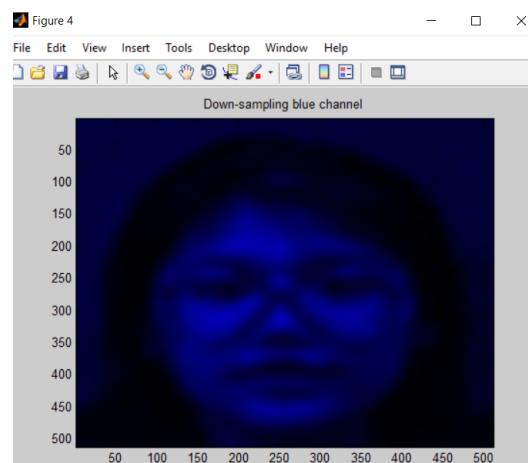


FIG 4.DOWNSAMPLING BLUE CHANNEL

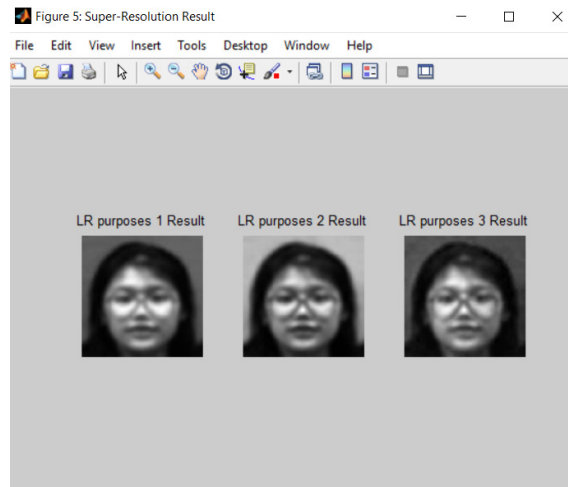


FIG 5.SUPER-RESOLUTION RESULT

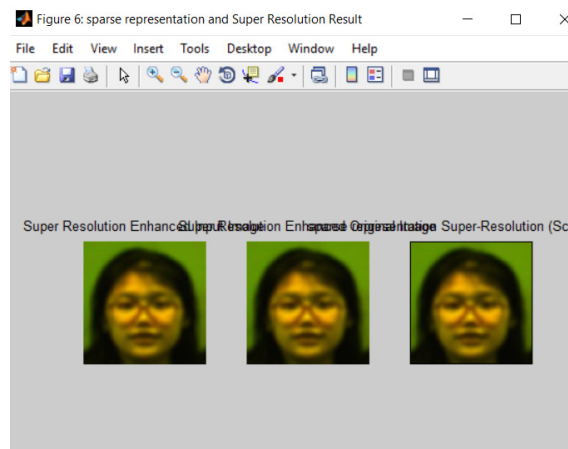


FIG 6.SPARSE REPRESENTATION AND SR RESULT

V. FACE RE-ID (GENERATIVE ADVERSARIAL NETWORK) GAN

In this part we focus on prototyping light weight deep neural

networks for LR face re-identification and showed that LR face images can be used for person re-identification. We employed data from a real surveillance system and conducted an extensive person re-identification study. GANs are basically made up of a system of two competing neural network models which compete with each other and are able to analyse, capture and copy the variations within a dataset. Several deep learning approaches use “Siamese” deep convolutional neural networks for feature extraction and metric learning at the same time providing novel end-to-end solutions. Face reidentification is a process of identifying a person using his/her face under consistent labelling across multiple cameras or even with the same camera to re-establish different tracks. These works help to motivate the LRFR problem as a component of the re-identification problem. [6] proposed a system in which an automatic anatomy segmentation method is proposed which effectively combines the Active Appearance Model, Live Wire and Graph Cut (ALG) ideas to exploit their complementary strengths. It consists of three main parts: model building,

initialization, and delineation. For the initialization (recognition) part, a pseudo strategy is employed and the organs are segmented slice by slice via the OAAM (Oriented Active Appearance method). The purpose of initialization is to provide rough object localization and shape constraints for a latter GC method, which will produce refined delineation. It is better to have a fast and robust method than a slow and more accurate technique for initialization.

SPP POOLING IMAGE

Using SPP-net, we compute the feature maps from the entire image only once, and then pool features in arbitrary regions (sub-images) to generate fixed-length representations for training the detectors.

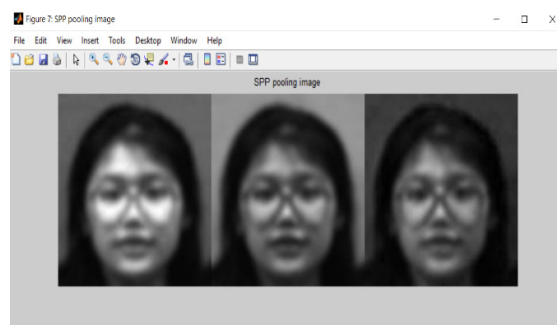


FIG 7.SPP POOLING IMAGE

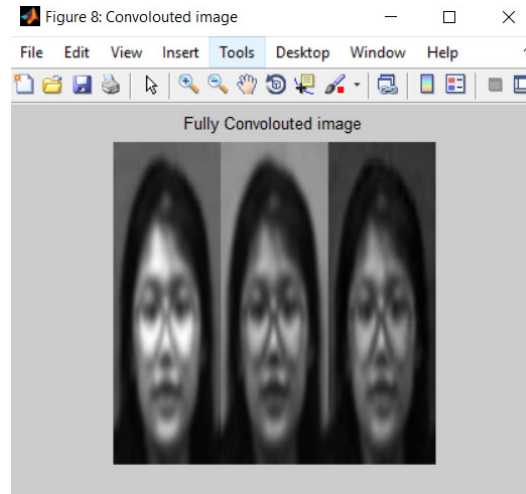


FIG 8. FULLY CONVOLUTED IMAGE

VI. OUTPUT

Both HR and LR Face Recognition images are obtained by processing several techniques and it is classified by using CNN.

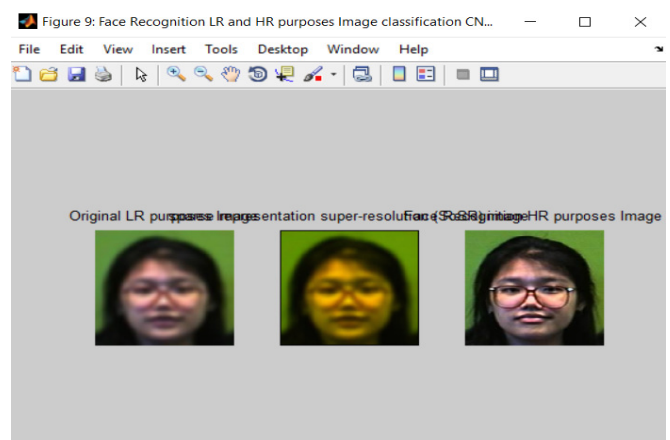
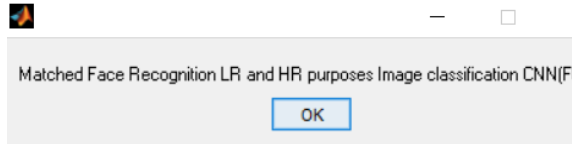


FIG 9. FACE RECOGNITION LR AND HR IMAGES

MATCHING LR AND HR FACE IMAGES



VII. TABLE

This table shows testing accuracy with different layouts.

Figure 10: Table Face Recognition LR and HR purposes Image classificat...

Face Recognition LR and HR classification CNN(FCN)	
sensitivity	92
specificity	98
CNN_Accuracy	99
Processing_Time	0.1888
Contrast	0.0541
Correlation	0.9876
Energy	0.2133
Homogeneity	0.9730
Entropy	0.0927
Feature_Data	

VIII. CONCLUSION

We provide several novel contributions. At first, we illustrate the performance gap between LR unconstrained face and LR constrained face recognition when using a super-resolution algorithm. Secondly, two important application scenarios based on LR face recognition are defined: unconstrained LR face identification and LR face re-identification which is done by

SPP pooling technique and convolution methods. Thus we obtained the face recognition of Conversions of LR images into HR images by matching with the given datasets.

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