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Cascading And Enhanced Residual Networks For Accurate Single-Image Super-Resolution

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Abstract: ***Recent years have witnessed the unprecedented success of deep convolutional neural networks (CNNs) and Generative Adversarial Networks (GANs) applied in single image super-resolution (SISR) tasks. However, CNN-SISR based methods often assume that the lower resolution (LR) image is downsampled bicubicly from its high resolution (HR) counterpart. It results in poor performance on images with degradations that do not follow this assumption. Here, we propose a framework to learn a residual image super-resolver that handles multiple degradations, improving its performance on natural images. Our basic premise is that the residuals between an upsampled LR image and the HR counterpart contain information about the true degradation and downsampling processes, controlled by particular image features. We show that learning residuals in image space leads to detail reconstruction improvement in many cases. In this work, we apply different CNNs/GAN-based models to learn and predict the residual image given the LR image. The residual to be learned is obtained by subtracting a bicubicly upscaled image of the LR image from the true HR image. The LR images are generated by applying a random blur degradation to the HR image followed by a bicubic downsampling. We also generate residuals from 3 different downsampling methods in LR image space dimensions to use as features. Finally, we show that our method is able to learn the spatially upsampled higher dimensional residuals and it can recover detailed HR images from bicubicly upsampled LR images by adding our proposed high resolution residual error.***

Keywords: Super Resolution. Downsampling. Convolutional Neural Networks. Gen- erative Adversarial Networks

I. INTRODUCTION

This thesis presents two new frameworks for image super-resolution via residual learning using deep neural networks with application to the public benchmark dataset of face images CelebA(LIU et al., 2016). The motivation for learning residuals and combining them to CNNs and GANs models arises from the assumption that, the distribution of residual images with respect to a pilot super-resolver, in the high resolution space, is better behaved than the unconditional distributions of high resolution images, in a fixed domain. GANs have achieved good results on approximating distributions, and hence simpler distributions like the residual images of high resolution faces from bicubic upscaled low resolution faces can be learned by these neural networks methods. In this chapter, we present the problem, our objectives as well as the main contributions we have achieved.

Contextualization and Motivation

Image super-resolution is a highly challenging task that has a wide range of applications, such as face recognition, satellite image understanding, and medical image processing, to name but a few. Super-resolution has been an attractive research topic in the last two decades and has been very successful at low upscaling factors (2-4x) with Generative Adversarial Networks (GANs). The input to a super-resolution GAN is a low resolution image (e.g. 16x16 pixels in size). The output from the GAN is a higher resolution image (e.g. 64x64 pixels in size). Kim, Lee e Lee 2016a adopted residual learning to address the problem of generating a high-resolution image given a low-resolution image, commonly referred as single image super-resolution (SISR). Another strategy proposed by Zhang et al. 2017 demonstrated that a single CNN model can handle multiple super- resolution scales, image deblocking and image denoising. Nevertheless, these approaches demand high computational cost due to the training step of deeper layers and the bicubic interpolation of low resolution images.
Despite impressive results in literature, recent deep learning methods still lack in practical applications, since they are normally trained in synthetic data sets. These datasets normally assume that a low resolution picture is generated via a deterministic downsampling method (LEDIG et al., 2017). As a matter of fact, real-world scenarios pose challenges for super-resolution because high resolution datasets are unvailable, downscaling methods are unknown and the input low resolution images are noisy and blurry (YUAN et al., 2018).

II. LITERATURE REVIEW

Traditional works have shown that patches in a natural image tend to redundantly recur many times inside the image, both within the same scale, as well as across different scales. Make full use of these multi-scale information can improve the image restoration performance. However, the current proposed deep learning based restoration methods do not take the multi-scale information into account. In this paper, we propose a dilated convolution based inception module to learn multi-scale information and design a deep network for single image superresolution. Different dilated convolution learns different scale feature, then the inception module concatenates all these features to fuse multi-scale information. In order to increase the reception field of our network to catch more contextual information, we cascade multiple inception modules to constitute a deep network to conduct single image superresolution.

Y. Sun Et-al, presented a compressive sensing based on a redundant dictionary has been successfully applied in super resolution imaging. However, due to the neglect of the local and nonlocal interactions of patches of a single image, the reconstructed results are not satisfactory in
noise suppression and edge sharpness. In this paper, we propose an improved method by adding steering kernel regression and a nonlocal means filter as two regularization terms and use an efficient clustering sub-dictionary learning scheme. We further demonstrate better results on true images in terms of traditional image quality assessment metrics.

Y. Sun Et-al, presented an observation for medical imaging and astronomical, high-resolution (HR) images are urgently desired and required. In recent years, many researchers have proposed various ways to achieve the goal of image super-resolution (SR), ranging from simple linear interpolation schemes to nonlinear complex methods. In this paper, we deal with the SR reconstruction problem based on the theory of compressive sensing, which uses a redundant dictionary instead of a conventional orthogonal basis. We further demonstrate better results on true images in terms of peak signal-to-noise ratio (PSNR) and root mean-square error (RMSE) and give several important improvements, compared with other methods.

M. Agrawal et-al, presented a technique for enhancing resolution of images by interpolating high frequency sub-bands generated using lifting wavelet transform (LWT) and spatial information of input low resolution (LR) image. Stationary wavelet transform (SWT) is used at intermediate stage for edge enhancement. The input image is decomposed using LWT in order to generate high frequency (HF) subbands. The generated HF sub bands are interpolated further. Different high frequency sub-bands obtained through SWT are added to correct the estimated HF sub bands. The input LR image is interpolated in parallel. All these sub-bands and estimated LR image are reconstructed by inverse lifting wavelet transformation (ILWT) to produce high resolution image. The qualitative, quantitative and visual images of the described technique show the superiority of the proposed method over conventional and state-of-theart methods. H. Ashikaga et-al, presented Single-image super resolution is a process of obtaining a high-resolution image from a set of low-resolution observations by signal processing. While super resolution has been demonstrated to improve image quality in scaled down images in the image domain, its effects on the Fourier-based image acquisition technique, such as MRI, remains unknown. We performed highresolution ex vivo late gadolinium enhancement (LGE) magnetic resonance imaging ($0.4 \times 0.4 \times 0.4$ mm3) in position fraction swine hearts (n D 24). The swine hearts were divided into the training set (n D 14) and the test set (n D 10), and in all hearts, lowresolution images were simulated from the highresolution images. In the training set, super resolution dictionaries with pairs of small matching patches of the high- and low-resolution images were created. In the test set, super resolution recovered high-resolution images from low-resolution images using the dictionaries. The same algorithm was also applied to patient LGE (n D 4) to assess its effects. Compared with interpolated images, super resolution significantly improved basic image quality indices ($P < 0.001$). Super resolution using Fourier-based zero padding achieved the best image quality. However, the magnitude of improvement was small in images with zero padding. Super resolution substantially improved the spatial resolution of the patient LGE images by sharpening the edges of the heart and the scar.

E. Faramarzi et-al, presented , a unified blind method for multi-image super-resolution (MISR or SR), single-image blur deconvolution (SIBD), and multi-image blur deconvolution (MIBD) of lowresolution (LR) images degraded by linear spaceinvariant (LSI) blur, aliasing, and additive white Gaussian noise (AWGN). The proposed approach is based on alternating minimization (AM) of a new cost function with respect to the unknown high-resolution (HR) image and blurs. The regularization term for the HR image is based upon the Huber-Markov random field (HMRF) model, which is a type of variational integral that exploits the piecewise smooth nature of the HR image. The blur estimation process is supported by an edge- emphasizing smoothing operation, which improves the quality of blur estimates by enhancing strong soft edges toward step edges, while filtering out weak structures. The parameters are updated gradually so that the number of salient edges used for blur estimation increases at each iteration. For better performance, the blur estimation is done in the filter domain rather than the pixel domain, i.e., using the gradients of the LR and HR images. The regularization term for the blur is Gaussian (L2 norm), which allows for fast non iterative optimization in the frequency domain. We accelerate the processing time of SR reconstruction by separating the up sampling and registration processes from the optimization procedure. Simulation results on both synthetic and real-life images (from a novel computational imager) confirm the robustness and effectiveness of the proposed method.

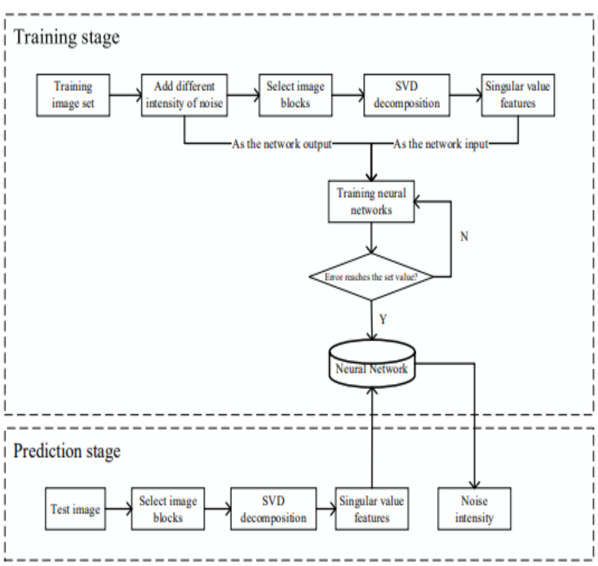
EXISTING SYSTEM

Filter-based methods this kind of method is usually use mean or median filter to filter the image, and then using the difference between the filtered restoration image and noisy image to estimate the noise. block-based methods , the basic idea is, the image is divided into several small pieces, and each piece of the standard deviation of calculated separately, a smaller portions of the standard deviation of mean value were calculated as the estimate of the noise of the image intensity. But this method based on image block didn’t considering the influence of the image edge details, and it has poor robustness. DWT transform-based methods this kind of method is using the characteristics of wavelet transform to estimate the image noise standard deviation .that image noise can be estimated using the equation sigma = MAD/0.6745 in the wavelet domain.But the estimated noise in this method will be large when the noise is small.

PROPOSED SYSTEM

We propose a noise estimation algorithm based on neural network and SVD decomposition framework. In the training stage, we add different intensity of noise on a group of noise free image, and then select a certain number of fixed size image blocks which standard deviation are minimum from these noisy images. After that, decomposing those image blocks using SVD decomposition, and take the decomposed singular values as the input vector of the neural network. At the same time, the noise standard deviation is used as the corresponding output to train the neural network. Therefore, the nonlinear corresponding relationships between the singular values and the noise standard deviation can been obtained for single-image super-resolution. In the prediction stage, it is also select some blocks from test image to estimate the noise intensity, and decompose those image blocks to get their singular value features. After that, inputting these features into the trained neural network, the output value is the estimation of the image noise intensity.

PROCESS FLOW DIAGRAM

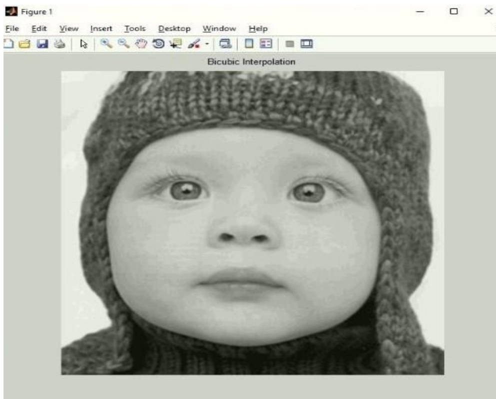


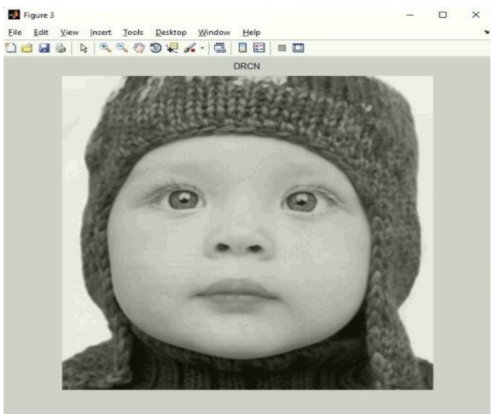
OUTPUT AND PARAMETER DETAILS:

1. Mask(s) - containing an overlay mask(s) of weak texture patches on the original input image - per channel and per processed slice
2. Note: If "generate masks" input parameter is set to "False", the masks zip file will be empty.
3. Report – image containing the values for number of patches, estimated noise levels and estimated signal to noise ratios:
4. Number of patches - number of extracted weak texture patches at the last iteration.
5. Estimated noise level - patch-based noise level estimation values, which are based on the following steps:

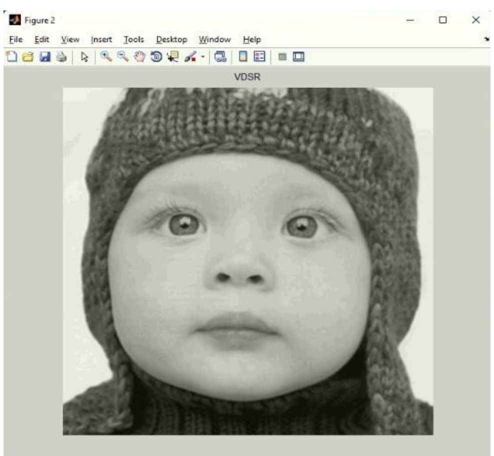
6. First, the algorithm performs a selection of weak-texture patches without high-frequency components based on gradients of the patches and their statistics.
7. Then, the noise level is estimated from the selected patches using Principal Component Analysis (PCA).
8. Estimated SNR - Estimated Signal-To-Noise-Ratio values (detailed and in increments of 5 for averaged values). This value is calculated as maximum image pixel intensity divided by the estimated image noise level. To avoid clipping artifacts, the maximum image intensity value is measured at the 95th percentile of pixel intensities.

RESULTS

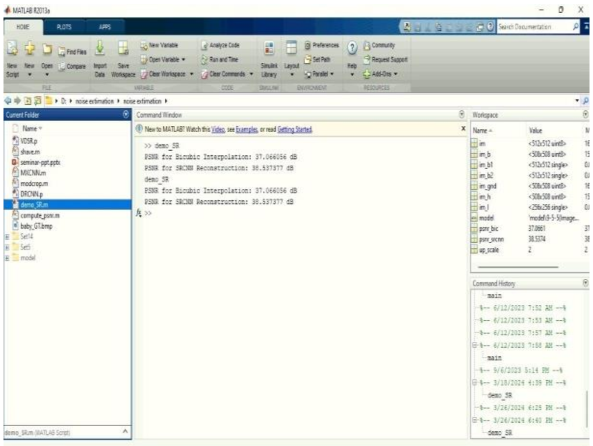




Super resolution Image



PSNR value for image



III. CONCLUSION

The singular values of image allows us to analyze the image content from different angles, and separates the main structural information of image from random noise to a certain extent. Combined with strong ability of nonlinear regression of the BP neural network, this paper puts forward a kind of accurate and efficient image noise intensity estimation algorithm. this algorithm can adapt to different kinds of noise, not only for images containing gaussian white noise can estimate the noise standard deviation accurately, the mixed noise can also achieved good results. algorithm of linear estimates, our nonlinear estimation algorithm based on neural network can achieve a more accurate result, and it also can be adapted to different size of images.

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