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Dynamic Approaches for Enhancing Single Image Super-Resolution Using Gradient Profile Sharpness Technique

V.Shanmugappriya
Student, Chettinad college of Engineering and Technology, Karur, Tamil Nadu India
E-mail: priyavenkat234@gmail.com

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Abstract - **In this paper, we propose an image super-resolution approach using a gradient profile prior, which is a parametric prior describing the shape and the sharpness of the image gradients. Generate high resolution image from a low resolution input image single image super resolution is used. Single image super resolution is used to enhance the quality of image. In this paper there is a image super resolution algorithm is proposed which is based on GPS Gradient Profile Sharpness. Indicate the superior performance of the proposed algorithm compared to the leading super-resolution algorithms in the literature over a set of natural images in sharp edges and corners.**

Keywords: **Single-image super-resolution, Gradient profile sharpness, Gaussian mixture model, Segmentation**

I.INTRODUCTION

The fundamental operations in image processing are the process of interpolation. The quality of image is mostly depend on the used interpolation technique [2]. In interpolation process the information of edge direction is very important[1].The interpolation direction is equal to the edge with the another edge. By using sequence of images to perform the interpolation super resolution interpolation can be improved[3]. In learning based approach we take low resolution image which is not clear by using this approach we compare this image to that image which is already stored in dictionary. The content which are lost in low resolution image are retrieve from that dictionary[1]. In Learning method with the help of training data set that predicate high frequency detail lost in LR image. learning method classified into 3 category. The gradient profile is a 1-D profile along the gradient direction of the zero-crossing pixel in the image. The gradient profile prior is a parametric distribution describing the shape and the sharpness of the gradient profiles in natural image. One of our observations is that the shape statistics of the gradient profiles in natural image is quit stable and invariant to the image resolution. With this stable statistics, we can learn the statistical relationship of the sharpness of the gradient profile between the HR image and the LR image. Using the learned gradient profile prior and relationship, we are able to provide a constraint on the gradient field of the HR image. Combining with the reconstruction constraint, we can recover a hi-quality HR image.

The advantages of the gradient profile prior are as follows: 1) unlike previous generic smoothness prior and edge smoothness prior, the gradient profile prior is not a smoothness constraint. Therefore, both small scale and large scale details can be well recovered in the HR image; 2) the common artifacts in super-resolution, such as ringing artifacts, can be avoided by working in the gradient domain. Our work is motivated by recent progresses on natural image statistics. The gradient magnitudes generally obey a heavy tailed distribution e.g., a Laplacian distribution. This kind of “sparseness prior” has been successfully applied to super-resolution[28], denoising , inpainting transparency separation and deblurring However, the sparseness prior only considers the marginal distribution of image gradients (e.g., intensity difference between two adjacent pixels) over the whole image. In this work, our gradient profile prior considers the distribution of the image gradients along local image structures. Fattal also proposed an edge statistics for image up sampling. The proposed statistics is the distribution of local intensity continuity in the HR image conditional on edge features in the LR image. Different from his non-parametric statistics, firstly, the gradient profile prior is a generic, parametric image prior for the gradient field of the natural image; secondly, our prior is stable to the image resolution. It is a good property for image super-resolution.

II.SUPER-RESOLUTION ALGORITHM

In Reconstruction method it require different patches from images then it resize the SR output. super resolution is the process of converting LR image into HR image[10] . Reconstruction based SR algorithm that will require the patches of image from one or more images when synthesizing the SR output[10]. statistical prediction model can be useful for single image super resolution. The model used to avoid any invariance assumption. This model to further enhance performance that suggest data clustering. Image super resolution are technique aiming at resolution improvement of images acquitting by low resolution sensors, minimizing visual effects. Recently several attempts have been made beyond the invariance assumption aiming at improving the stability of recovery. The statistical model and the basic single image SR scheme: The main motivation of this model to suggest the desire predict for each LR patch .The missing high resolution detail This is mainly for two reasons first is the aims at characterizing signal of different quality, so it use fewer atoms for the lower quality contend. second is Use for avoiding high complexity sparse coding computation. In this paper GPS is used to maintain gradient magnitude and spatial scattering of gradient profile then two models that is triangle model and Gaussian mixture model is proposed. Profile shape and profile gradient magnitude is maintained based on gradient profile transformation. Finally HR image is generated from transformed gradient profile. That image added as a image prior in HR reconstruction image 2. Related Work Gradient profile is for describing the shape and sharpness of image when we convert low resolution image into high resolution image the gradient profile is used for edge sharpness[12]. gradient profile prior are used for improving the low resolution of image[6].For interpolation of the image the several information on the sparsity of image has also useful[5].Reconstruct a high resolution image by using low resolution image is the aim of image interpolation[3].for recovering sharp edges of low resolution image the image super resolution will be use. when we convert the image from low resolution to high resolution it will be useful in many application such as medical image diagnosis, computer vision, satellite imaging and also in entertainment. Because of the imaging environment and the expensive imaging equipment when we capture the HR image by using CCD and CMOS it is difficult to getting an image at the desired resolution level. so because of this many super resolution methods are developed[8]. Low resolution image is the down sampled and blurred version of original HR image . To improve the resolution of given image SR technique are used. There are two types of edges first is roof edge and ridge edge.

III.GRADIENT PROFILE PRIOR

Previous natural image statistics characterizes the marginal distribution of the image gradients over the whole image. The spatial information is discarded. Instead, we study the image gradients along local image structures and the statistical dependency of the image gradients between the HR image and the LR image.

A. IMAGE ENHANCEMENT

Image enhancement operations improve the qualities of an image like improving the image's contrast and brightness characteristics, reducing its noise content, or sharpen the details. This just enhances the image and reveals the same information in more understandable image. It does not add any information to it.

B. IMAGE RESTORATION

Image restoration like enhancement improves the qualities of image but all the operations are mainly based on known, measured, or degradations of the original image. Image restorations are used to restore images with problems such as geometric distortion, improper focus, repetitive noise, and camera motion.

C. COLOR TRANSFER:

It is the way to match the means and variances between the target and the reference in the low correlated color space. This approach was efficient enough, but the simple means and variances matching was likely to produce slight grain effect and serious color distortion. To prevent from the grain effect, Chang et al. proposed a color category based approach that categorized each pixelas one of the basic categories. Then a convex hull was generated in color space for each category of the pixel set, and the color transformation was applied with each pair of convex hull of the same category.

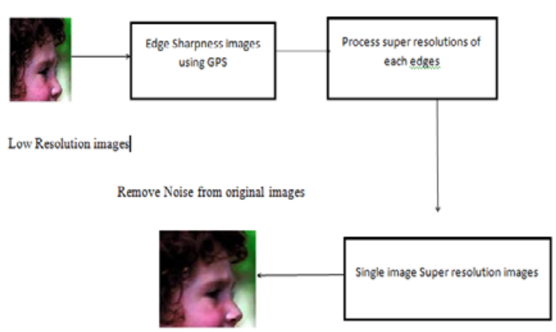

Fig. 1 Remove Noise from original images Texture

D.LR-HR PATCH PAIRS

LR patch is a sparse convex combination of LR patches in a dictionary, the corresponding HR patch may be estimated using the same convex combination of HR patches in the dictionary. This is obtained by learning a coupled dictionary in LR-HR patch feature space. The effectiveness of such sparsity prior for SR image reconstruction is demonstrated by Yang et al. [11]. There are a number of extensions of this sparse estimators available in the Instead of single sparse dictionary, incorporated multiple dictionaries for a more detailed prediction. Wang et al. proposed a semi-coupled dictionary learning model where the two dictionaries are not fully coupled to give flexibility to the mapping function for converting an LR image to a HR image. Dong et al. proposed a non-local autoregressive model, which imposes more structural constraints on the missing pixels to the sparse estimators. They claimed that their model could reduce much the coherence between the sampling matrix and the sparse representation dictionary. On the other context, in the last few decades, there has been a growing research interest in the applications of soft computing techniques, such as neural networks and fuzzy systems, to the problems in digital image processing. That includes image filtering image segmentation image classification and image interpretation Several fuzzy filters such as the iterative fuzzy control based filters and the GOA filter for noise reduction have already been developed. Most of these state-of-the-art filtering methods are mainly developed for the reduction of fantailed noise like impulse noise. Also there are fuzzy techniques that produce convincing results for additive noise, which is illustrated in and.

Neuro-fuzzy (NF) systems offer the ability of neural networks to learn from examples and the capability of fuzzy systems to model the uncertainty which is inevitably encountered in noisy environments . Chen and Wang developed an image up-sampling technique using fuzzy sets. They presented a framework to improve the effectiveness of traditional interpolation methods. They replaced the original euclidean distance in the interpolation formula by an adaptive distance based on local gradient information obtained by combining fuzzy set theory with genetic learning algorithm. However, their method does not learn the direct LR-HR relationship from the training database and is just an improvement over traditional interpolation based methods. Fuzzy rule-base systems allow representing the imprecision which is inherent to the definition of certain concepts. For instance, the concept close to is intrinsically vague and imprecise, and its semantics depends (i) on the context in which objects are embedded, (ii) on the scale of the objects and (iii) of their environment. Fuzzy systems also allow managing imprecision embedded in the experts knowledge of the concerned domain. They constitute an adequate framework for knowledge representation and reasoning, reducing the semantic gap between symbolic concepts and numerical data [35]. Fuzzy rule based systems are suitable for the development of the learning algorithms for computer vision/image understanding because they, being a nonlinear knowledge-based methods, are able to deal with ambiguities in a robust way.

IV.THE GRADIENT FIELD TRANSFORMATION

We propose a gradient field transformation approach to approximate the HR gradient field by transforming the LR gradient field using the gradient profile prior. . Super-resolution comparison (4X) of learning based method [, alpha channel super-resolution [6], and our approach. Both large scale edges and small scale details (on the face) are recovered in our result.

Fig. 2 Transformed gradient field is much closer to the ground truth gradient field of HR image.

Our reconstructed result has rare jaggy or ringing artifacts.

Algorithm: Single-Image SR Algorithm.
1: *INPUT*: A LR Test Image, Cluster Dictionary Pairs.
2: *OUTPUT*: A HR Image Estimate
3: Divide the LR image into overlapping patches.
4: Up sampled the LR image to the MR resolution level.
5: Apply feature extraction filters (first and second order gradient) on the MR image.
6: Divide the extracted features into patches and vectorize them.
7: for Each MR patch do
8: Calculate SM and DPA of the MR patch and determine the cluster.
9: Sparsely code the MR patch features over the cluster LR dictionary.

10: Reconstruct the corresponding HR patch by multiplying the HR dictionary of the same cluster with the sparse codes of the MR features.
11: end for
12: Merge overlapping patches to obtain a HR image estimate.

V.CONCLUSION

In this paper, we propose a new single-image super-resolution algorithm based on multiple structured cluster dictionary pairs is proposed. Clustering is done with the magnitude and the phase of the gradient operator of image patches. This is done by classifying patches based on their spatial sharpness using the magnitude and then sub-clustering these patches based on their directionality using the phase of the gradient operator. For each cluster, a pair of compact dictionaries is designed. For each low resolution patch, a cluster is selected using these measures, and the cluster dictionary pair is used to reconstruct a high resolution patch. The proposed clustering allows for applying bicubic interpolation to super-resolve patches of insignificant high frequency components, thereby reducing the computational complexity of the proposed algorithm. Besides, one can afford to design compact cluster dictionaries. Numerical experiments validate that the proposed algorithm is competitive with the leading super-resolution algorithms in terms of PSNR and SSIM, at a competitive computational complexity.

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