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CHANNEL WISE GRADIENT DESCENT METHOD FOR SINGLE IMAGE SUPER RESOLUTION

Vadla Mahendrachari[1], Shaik Taj Mahaboob[2]

[1]*MTECH student, Department of ECE, JNTUA college of Engineering pulivendula,*
[2]*Assistant Professor, Department of ECE, JNTUA college of Engineering pulivendula,*

Abstract*— In this article, we propose a new method that achieve super resolution of an image which uses a channel wise gradient descent approach to obtain high resolution version image from low resolution version of the image. In this technique we first apply bilinear interpolation further divides the low resolution colour image in to R, G, B channels then apply the gradient decent approach to individual channel by using a set of rules and finally producing the high resolution image. The proposed approach provides high PSNR value and relative SSIM as compared to the existing methods.

***Keywords*— Image super-resolution, Gradient Descent, PSNR, SSIM, LR image, bilinear interpolation, and high resolution image.**

I. INTRODUCTION

The Super Resolution methods are a class of practices that increases the spatial resolution of the scene. The major purpose to obtain the super resolution is for improving picture quality of an image for further application. It is often required, a high resolution image in surveillance and other sectors but limiting to physical constraints of imaging system. Image quality is degraded due to decrease in amount of light available and aggregation of shot noise. To get a high quality image there are two basic things, one is the imaging system which uses better image sensors and high diffracting lens. The other one which uses computational algorithms by means of digital processing. In this direction several algorithms are proposed from last decades by means of digital processing systems.

There are basically two types of super resolution techniques are there depending on the low light image scenes available for process those are super resolution by using single image scene and another is super resolution using multiple scenes of same image. In many times the availability of multiple scenes of same images are doesn't exist, so the super resolution methods those are based on single image scene are convenient to develop a high resolution image.

There are several types of techniques are used to produce a high resolution version image from low resolution version image generally classified as interpolation based up scaling techniques, reconstruction based super resolution methods, learning based super resolution methods.

The basic techniques, those can be used to produce high resolution images are the interpolator types, here the new pixels are inserted between the existing pixels these results increasing the resolution. Those are nearsest neighhour, bicubic ,bilinear [1], these methods are widely used because of their ease and lower complication .but these methods are non adaptable to the content of the image and also limited to complex structures because they introduce aliasing and over smoothening sections in image.

The another type of methods achieving super resolution are reconstruction based by using image priors like, sparsity[2]-[7] ,Gaussian mixtures[8] and self similarity [9]-[6]those are power full to produce high quality images with increased cost of computational complexity.

In recent days the [4] ,[6],[13],[14]example based resolution methods has plays an attention . The main idea behind these techniques is to use the external database for achieving super resolution it includes the training section and test section .in training section the mapping can be done between lr patches to hr patches a dictionary of relative mapping can be produced these dictionary is used to produce hr image at the test phase.

The Anchored neighborhood regression (ANR)[5]produces high quality images while significant increase in speed ,these can be achieved by replacing sparse coding step in learning of dictionaries with ridge regression problem outcomes(filters).by following these the A+[6]advances the concert of ANR by learning from closest dictionary particle with addition learning of locally nearest training samples.

The SRCNN[15] is the another proficient example based method that can be developed by using convolutional neural networks[16],learns end to to end mapping from Low resolution images to HR images .The SRCNN method is a complex algorithm to produce high resolution because of using the neural networks which are very complex in structure.

The another type of learning based type that can be proposed recent days [20] that uses wavelets to learn mapping of low resolution patches in the direction of the high resolution patches. The wavelet based super resolution are also the complex by preserving high resolution pixels.

II. PROPOSED SYSTEM

In this segment we briefly illustrate about our proposed system .Our proposed system developed by using the fact that any color image is the combination of red, blue, green color channels. Each individual channel can be processed and combining these processed channels produces a high quality image.
The block representation of the process of our proposed system is shown in below block diagram.

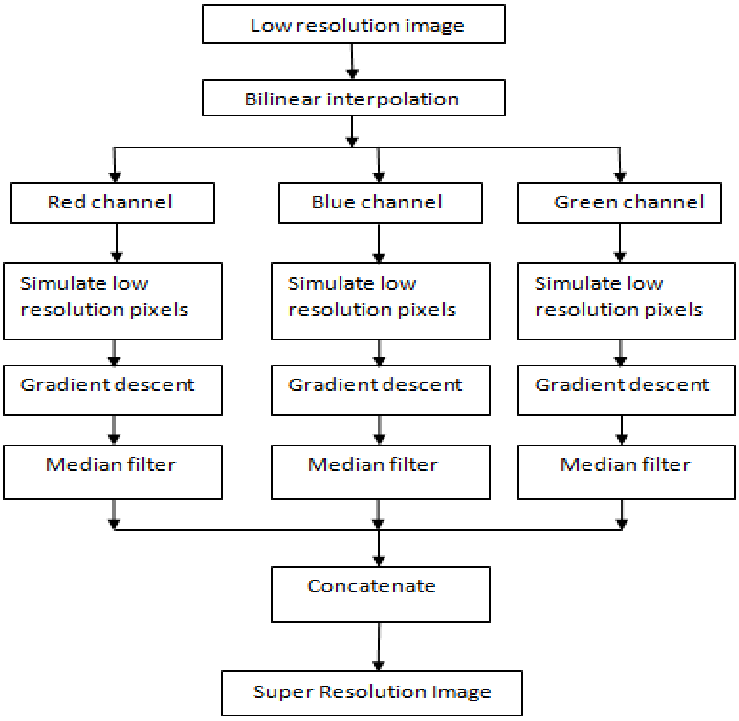

Fig1: block diagram representation of channel wise gradient descent process for single image super resolution.

Initially the low resolution image can be bi-linearly interpolated for up scaling the images then the color image can divided in to three chrominance channels viz R,G,B channels .each chrominance channels are processed by parallel in the direction as follows. The low pixels are stimulated the low resolution pixels. Further they applied to the gradient descent algorithm which gives the local minimum between pixel values. The descent algorithm block output is applied to the median filter which removes the noise from the image by preserving the edges of the image. Then finally the all chrominance channel parallel outputs are jointed to get the high resolution image.

III. DETAILS ABOUT THE PROPOSED METHOD

In this segment we give the information of our proposed System.

Low resolution image:
The low resolution image is an image or screen which consists of small amount of pixels, causing the image to be jaggy is taking as the input image in our system. Normally it can be taken from an imaging system which captures the physical structures in to an image often surfers with lower quality level. Our main purpose is that to increase its resolution with spatial enhancement that means increasing the quality of a image.

Bilinear interpolation:
This is an interpolation method in this the new pixels are inserted between the existing pixels the new pixels values can be obtained by using the average of nearest four neighbour pixels. It is simple method to up scaling an image. But increasing the scaling level causes aliasing artefacts because of over smoothing.

R, G, B Channels:
Every color image is a combination of RGB channels. In our proposed system the image is first divided in to three chrominance sub channels because it is simple to apply the algorithms to the monochrome image compare to color image. We processed these channels as followed then combining the resulted three monocratic images forms the high resolution an image

Simulate low resolution pixels:
In this section we can represent the sub channels in to the mono chrominance images for further processing.

Gradient descent algorithm:
It is a first order iterative type optimization method for evaluating the least value of a function. It is based on a convex function that tweaks its parameters iteratively to minimize a given function to its local minimum. The equation below describes what Gradient Descent does:

$b = a - \gamma \nabla f(a)$
'b' describes the next position of our climber, while 'a' represents his current position. The minus sign refers to the minimization part of gradient descent. The 'gamma' in the middle is a waiting factor and the gradient term ($\Delta f(a)$) is simply the direction of the steepest descent algorithm.

This approach performs steps in accordance with the negative of the gradient otherwise approximate gradient of the function at the current point. If as an alternative one performs steps proportional to the positive of gradient, the value approaches a local greatest value of that function; the process is then known as gradient ascent method.

Median Filter:
The gradient processed descanted image is applied to the median filter to decrease the noise from the image. The median filter, that is a non-linear filter that is used to reduce the noise .It uses the median of the pixels to remove the noise in image and it has the ability to preserve the edges of an image. Because of the above property the median filtering process is commonly used in digital image processing. In some applications it is used as pre-processing step to improve the further processing like edge detection in an image under test..

Concatenate:
The images from R, G, B channels are concatenate to obtain the final image. Concatenation is the process, that capture two or more separately placed objects and then places them alongside next to each other with the intention that they can now be treated as one object. Hence R, G, B images which are obtained from median filter is concatenate to obtain final output.

Super Resolution Image:
The overall productivity is the high resolution image with increased spatial resolution .The essential work of *Super-Resolution* (SR) is to produce a higher *resolution image* from single lower *resolution image*. High *resolution image* offers a high pixel density value and there by more details about the original image. Hence, the high resolution version of an image is obtained by using Gradient descent approach.

This approach has an advantages those are it is simple to produce high resolution version image from a single low resolution version image. Because of it simply uses the iterative algorithm to find local minimum. It has several applications in the fields of machine learning, medical image analysis and so on.

IV. EXPERIMENTAL RESULTS

Here, we analyses the concert of our proposed system by comparing wave let based super resolution method with the parameters SSIM and PSNR .That we use a Set 5 images proposed given in [18] for evaluating the PSNR(peck signal to noise ratio) and SSIM (structural similarity).the table 1 shows the SSIM and PSNR results comparison table.

Figure 1: input image

Figure 1: bilineared image

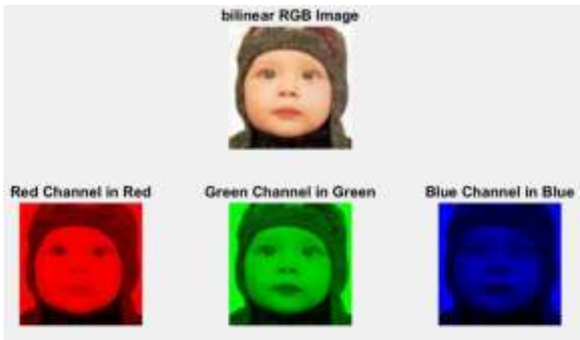

Figure 3: chrominance sub channel images

Figure 4: super resolution image

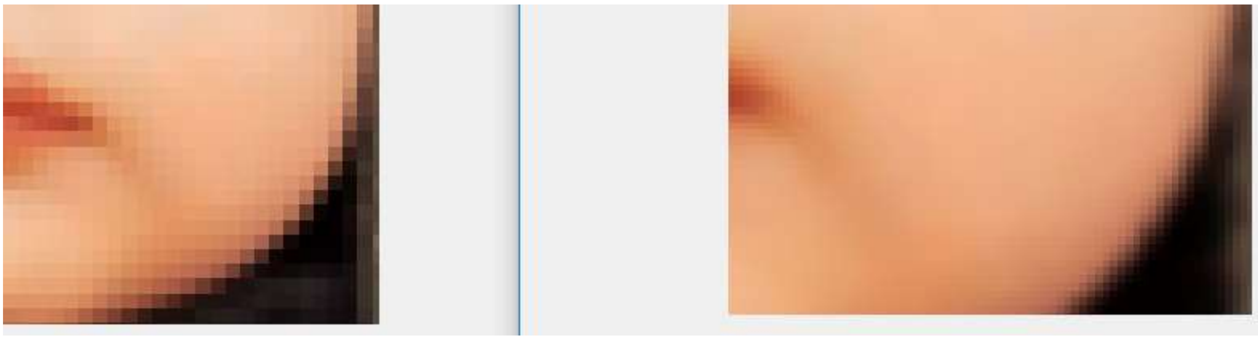

Figure5:comparision between input image and resulted image

Table 1: SSIM and PSNR results for set5 images by wavelet based and proposed super resolution methods.

Images	Wavelet based image super resolution[21]		Proposed method	
	SSIM	PSNR	SSIM	PSNR
Baby	0.97	24.41	68.0137	0.98
bird	0.96	19.59	69.6495	0.98
butterfly	0.92	12.16	69.394	0.98
face	0.9745	26.28	75.86	0.98
lady	0.9469	17.64	76.71	0.98

V. CONCLUSIONS

In our proposed method, the single image super-resolution can be attained by applying gradient descent approach to the chrominance channel followed by median filtering that removes the noise and also preserving the edges. Finally we combined the processed chrominance channels to get high- resolution image. Our method shows increasing the PSNR value with almost preserving structural similarity compared to the recent algorithms, by giving the high denoising performance with less artefacts. Our proposed technique can be used for further processing for applications like surveillance processing, object detection and the applications where high quality images required from low resolution image.

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