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Single Image Super Resolution using Direction let Transform and Directional Variance

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Abstract

Super-resolution technique is defined as recovering missing spatial frequency information from a low resolution image to retrieve its high resolution image(HR) which is equivalent to the original scene . Similarities between low resolution image and high resolution image blocks are learned, and are used in the low resolution input image to retrieve the high-resolution version. In this article the authors propose a single frame super resolution method using a skewed anisotropic wavelet transform , called Directionlets Transform. The proposed method can be used for live image processing applications. Available method [2] which is based on directionlet transform is computationally very intensive. In this paper using directional variance method, the directionlet method is modified which further reduces the computation and time.

Keywords : Directionlet, anisotropic, super resolution, lifting, directional variance.

I. INTRODUCTION

The image processing applications in forensic science surveillance, medical diagnostics, satellite imaging, object identification which requires high frequency information. It is clearly obvious that the above mentioned applications give better result if the images contain more information. The super resolved images deliver the user extra information which is useful in many cases. The major things which influence the captured image quality are the sensors, the image acquisition environment conditions, optical technology used, etc. and so the captured photo will lack information. This problem is considered as inverse problem that explains the process of retrieving a HR frame which overcomes physical constrains [1]. This technique contains process like up sampling the image which increases pixel density and also reducing artefacts which occurs during the process of capturing the image ,like aliasing and blurring. Normally the Standard interpolation techniques consider low resolution data and the interpolation techniques improves the pixel density and does not add more data. The resultant image will be blurred and noisy. The problem of these upsampling techniques is that sharp features in the image will be blurred. A new super resolution method based on conventional directionlet transforms is proposed by the authors in paper [2]. In this paper, the conventional directionlet transform based technique is modified based on the concept of directional variance, thereby further reducing the computation and time.

II. RELATED WORK

The input low resolution image obtained using a low-resolution camera is super resolved using learning based super resolution algorithms. These algorithms use a training set which is formed using details of available high-resolution images. The details of images are stored as coefficients of feature representations like wavelet transform, Discrete cosine transform, directionlet transform etc. Single frame image super resolution can be used in different applications where database of high-resolution images is available. This technique is classified under the motion free super resolution scheme. In their article [3], authors present many analytical result sequence which confirms that as zooming factor increases, retrieval constraints give very few useful information. Freeman et al introduces an algorithm based on Bayesian propagation using Markov model, which is a new learning based super resolution technique. The authors[9] introduce a super resolution method using different zoomed images from a camera. With the help of sequence of images with multiple zooming factors of a shot, authors retrieve an image of the full shot at a resolution equivalent to the most zoomed observation. In the article [6], by using the wavelet transform the authors present a single frame, learning-based super-resolution restoration method to describe a handicap on the solution. In the article [5] authors also introduced a method using the contourlet transform which can capture the smoothness on contours applying directional decompositions namely learning-based, single-image super resolution reconstruction. In their article[11], authors tried to elucidate this super resolution complication when the general natural images (GNIs) made by super resolution methods. In their presentation[12] comparisons of standard interpolation methods and two learning based super-resolution algorithms are made by Isabella. In the paper [5] authors study about different local and global, learning-based, single-frame image superresolution reconstruction methods in dealing three peculiar tasks and their functionalities. In their paper[9] Freeman et al presents a new technique to eliminate the ramifications of camera shake from seriously fade images. In the paper[10] author described the application of learned kernels to super resolve using discrete cosine transform in support vector regression. The authors describes a new method which depends on prior of image in the form of a p.d.f based upon sampled images[5].

In this article [8] authors mention dense feature fusion (DFF) for example based super resolution. In their presentation [2] authors present a new leaning based technique using directionlet transform. In this paper the above mentioned method is modified with the theory of directional variance.The directional variance is applied to find the pair of the transform directions to implement directionlet transform .

This paper is categorized as follows. The theory of Directional transform are depicted in Section 3. This portion describe theory of lattice based transform and directional variance in the execution of Directionlet transform . In section 4 new method is presented. In the section 5 , the implementation and results are explained with commonly used grey-scale images. In the same section the results are compared with standard interpolation techniques .Finally, conclusions are given in Section 6.

III. DIRECTIONLET TRANSFORM

The directionlet transform is skewed transform. In the skewed transform directions are choosed according to the image information not necessarily along the standard directions as in the case of wavelet transform. It is proved that directionlet transform provides an effective means to analyze and represent images. Another specialty is DT is anisotropic which means number of transforms in selected directions are not equal .[7] .

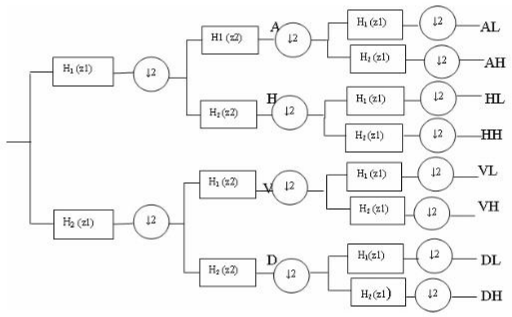

Fig 1 *Filter bank representation of directionlet transforms*

The directionlet transform is obtained by repeating the different steps in the lower band . Anisotropic transform is described as AWT(p1,p2). Figure 1 shows filter bank representation of Directionlet transform, AWT(2,1) were p1 = 2, p2 = 1.

Directional variance

For an image, information content locally changes in different directions. Images are divided into small blocks since in an image information locally changes in different directions. As already stated, the transform directions are along selected pair of directions. In this method, the suitable pair of directions for the image block are selected using the concept of directional variance. That is the directional variance concept is used to find the suitable pair of directions. Along the digital lines with slope s in the input patch X, the directional variance is calculated as[13]

$$dirvariance = \sum_{i=1}^{n} X$$

$$v = \sum_{i=1}^{n} \sum_{j=1}^{k_i} ((X_j - X_L(r,i))^2$$

Here X_j is the pixel in the selected digital line L(m,r) and X_L(r, i) is obtained by taking mean of the pixel values in the line L(s,r) with slope s. In the image patch X, N is the total pixels and n gives how many lines are included in the selected patch .

IV. THE CONVENTIONAL DIRECTIONLET BASED SUPER RESOLUTION METHOD CAN BE SUMMARIZED AS FOLLOWS .

1. The low resolution image is obtained by taking the average of every 2 x 2 pixels in the available high quality image obtained from a high resolution camera.
2. The obtained images are divided into patches of small size. The small patches are overlapped with nearest neighbor patches . Energy value of LR patch is calculated and this value is used to normalize the contrast of each individual patch.
3. The transform is implemented in selected pair of directions. After finding the pair of directions according to the image information, the directionlet transform is obtained . The coefficients of low resolution patch and corresponding high resolution patch are saved in the training set in five groups . In this paper the training set contains five groups of coefficients according to the transform directions. The selected pair of directions are (0^0 ,45^0), (0^0 ,-45^0), (90^0 ,45^0), (90^0 ,-45^0), (0^0 ,90^0).
4. Directionlet transform is applied to the small partitioned blocks in the given LR input frame, along its selected pair of directions.
5. Applying minimum absolute difference criterion, Coefficients of Directionlet transform of input Low resolution image and those in training set are compared.
6. After the comparison, the patch with minimum difference is obtained and its corresponding high frequency coefficients is used as the missing high frequency bands for the unknown HR patch.
7. By taking the inverse directionlet transform of cubic spline interpolated LR patch and obtained high frequency bands the high resolution image is obtained and the contrast normalization is undone.
8. The remaining input patches are also undergone the above process.
9. Directionlet transform is implemented in selected pair of directions.

V. SELECTION OF DIRECTIONS

From five sets of directions D = (0^0 ,45^0), (0^0 ,-45^0), (90^0 ,45^0), (90^0 ,-45^0), (0^0 ,90^0), for each block the suitable pair of directions is selected. For the low resolution image and its corresponding high resolution image a directional map is developed by assigning best pair of transform directions for each image patch. For the Figures 2 (a) and (c), the directional map is Figures 2(b) and (d). The best suitable pair of directions for each patch in the low resolution image is given by the directional map. The directionlet transform is applied in each patch along these five set of directions to find the best pair of directions. The best pair of directions d_n is selected for each patch indexed by n using equation

$$d_n = \arg\min \sum_{n,j} |W_{n,i}|^2$$

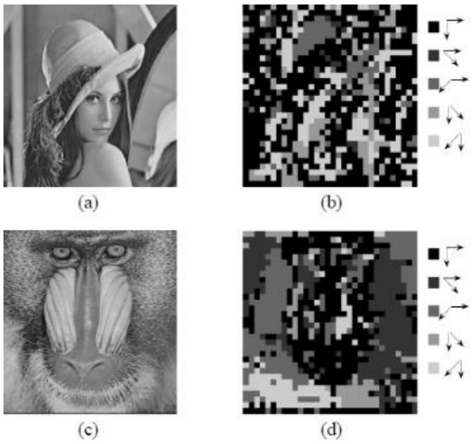

***Figure 2:** (a) The original image Lena (b) Its corresponding directional map(c)*

The original image Baboon (d) its corresponding directional map

Where the directionlet coefficients $W_{n,i}$ are obtained by applying directionlets to the n th patch along the pair of directions dn. Here using the directional map determined by the set D minimizes the energy in the high-pass sub-bands and the best matching between transform and locally dominant directions across the image patches are provided. As the size of the training set increases, the computing time also increases, which is the disadvantage of this method. So using the concept of Directional variance, this method is modified.

Directional variance method

Suitable pair of directions must be selected to apply the directionlet transform. The selected directions are 0^o, 45^o, 90^o and -45^o and the the directional variance is computed along the rational directions (i, j) = (1, 0), (1, 1), (0, 1), (-1, 1). To implement the directionlet transform the pair of directions is selected by identifying the directions corresponding to the two minimum directional variances. Directional map of that low resolution and high resolution images is formed by assigning transform directions with minimum directional variance of each patch.

VI. IMPLEMENTATION

Using available high-resolution images downloaded from the internet is used as the training set which involves various levels of details. For the experimental purpose, the input low resolution image is obtained by down sampling available HR image averaging every 2x2 pixels. db4 wavelet basis is used to implement the directionlet transform. The magnification factor for super resolving the low-resolution image is 2.

VII. RESULTS AND DISCUSSION

As already stated a training set used here contains different information obtained from good quality images, using this training set different grey images are super resolved . The time required to form training set and super resolving the image is shown in the table 1 . The signal to noise values needed to super resolve an image of size 256x256 to the size 512x512 are 20.34dB and 20.35dB using convolution based directionlet method and new directional variance method respectively. The time taken to super resolve an image of size 500× 233 to its double size with conventional directionlet method is 3684.766seconds. At the same time the new method requires 3017.22 seconds for the super resolving process. The convolution based directionlet method takes 1142.806 seconds to super resolve an image with 128 × 128 size to the size 256 × 256, at the same time the new method requires only 803.2seconds.

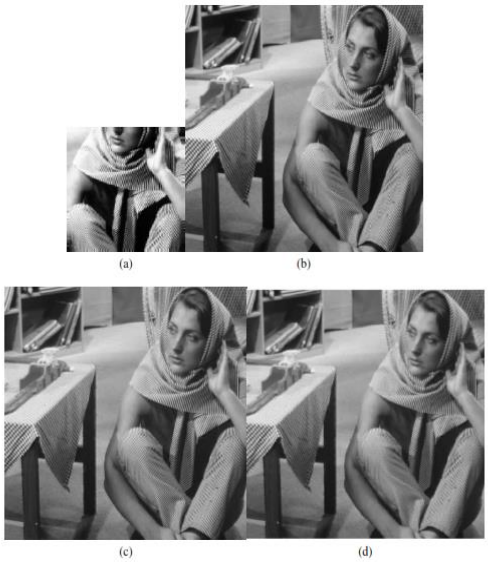

***Figure 3:** (a)input image (b)Original High resolution image(c)Resulting image with new directionlet transform method(d)Resulting image using directionlet transform*

Table 1: *Time taken to super resolve low resolution images of different size with new directionlet method and traditional directionlet method.*

Input images		time in seconds	
name	size	Directionlet method	directional variance based directionlet method
image 1	500x233	3684.766759	3017.22
image2	128x128	1142.806190	803.2
image3	256x256	1841.033	1073.23

VIII. CONCLUSION

Directionlet transform is proved to be an efficient tool for analyzing and representing two dimensional signals like images. The new method uses directional variance concept for finding the suitable directions which is required for implementing the new skewed anisotropic transform. Result shows that the computation time is reduced considerably in this new technique. The less complexity and time reduction achieved by combining directionlet transform and directional variance concept will be effective in live image processing applications.

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