

Video Enhancement using Non Subsampled Contourlet Transform and bilateral Filtering Techniques

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Abstract: This paper introduces a new approach for video super resolution problem. To this end Compressive Sensing (CS) theory along with Non subsampled Contourlet transform has been used. In CS framework the signal is assumed to be sparse in a transform domain. An approach has been suggested using this fact in which Contourlet domain is used as the transform domain and a CS algorithm helps to find the high resolution frame. A post processing step is applied afterward to the estimated outputs to increase the quality. The post processing step consists of a de-blurring using bilateral filter for increasing the consistency. This method helps to relax the conditions on hardware and increase the quality of the video after capturing, in fact the quality of the video streams in consumer applications can be increased even the capturing device represents the scene in a low resolution format. Experimental results show significant improvement over existing super resolution methods in both objective and subjective quality.

Keywords: Frame separation, Bi-lateral filter, Non-Subsampled Contourlet Transform (CT), Bicubic Interpolation, Adaptive filter, Reconstruction.

I. INTRODUCTION

Video improvement drawback will be developed as follows: given associate degree input quality video and also the output top quality video for specific applications. How can we make video more clearer or subjectively better? Digital video has become an integral part of everyday life. As the use of large displays is increasing, the demand for higher quality videos is growing fast in consumer market. New devices have been implemented to capture images and videos with much finer details. To this end more powerful optics and complex image stabilization mechanisms are required. Although many improvements have been made over the capturing devices and cameras, further enhancements are subjected to hardware complexity and restrictions.

In many applications including cell phone and webcam the imaging sensors capture low resolution images due to low cost sensors or physical limitation of the hardware and then a software alternative improves the quality of the captured frames. There are techniques to increase the resolution in an offline manner after that the image or video has been captured. Super-resolution (SR) is among techniques to improve the quality of the images received by the users of consumer applications such as video streaming on the Internet, cell phone devices and video conferencing. Super Resolution makes a high resolution frame out of one or a set of Low Resolution (LR) frames. In fact in low resolution pictures the high frequency elements are lost and SR tries to estimate those missing frequencies in a very approach that the difference between the first image and also the re-constructed SR is minimum.

There are different methods to generate HR images from the LR ones. Some methods used the reconstruction based approaches and some others use the learning algorithms. Reconstruction based approaches use the information in separate frames for solving the problem of SR. In fact these methods use the independent information in different frames and fuse them to make one HR image. Projection onto Convex Sets (POCS) [2] and Iterative Back-Projection [3] Methods are among the famous SR+ methods in literature. Learning based approaches use a specific image sequence set to learn their characteristics and use those known characteristics as extra information to reconstruct the HR image. Recently there are some new methods introduced which only use a single LR image for finding the HR image.

Image interpolation could be a resolution for generating a HR image from the associated LR capture. It is currently used in consumer applications such as medical imaging and up conversion of standard definition video frames. Some

algorithms like bi-linear and bi-cubic are simple and quick in implementation however they fail to capture the variable element structure around edges, as a result the picture would be blurred and with ringing artifacts around edges. With the increasing demand for higher resolution images a lot of powerful ways for interpolation were planned to preserve edge sharpness and turn out images with fewer artifacts. An edge directed interpolation was presented by Li and Orchard where the authors estimate the covariance of the HR image from the variance of the LR image [5].

Zhang et al proposed a method in which a missing pixel was interpolated in multiple directions and the results were fused by minimum mean square-error estimation [6]. An up scaling approach for resizing images in the DCT transform domain was proposed by Park et al [7]. The paper uses the property that the multiplication in spatial domain corresponds to the symmetric convolution in DCT domain.

Sen et al use the sparsity of an image in the wavelet domain and Compressive Sensing (CS) theory to interpolate the HR image [8]. The sparse mixing estimator method [9] proposed a new class of adaptive estimators acquired by mixing a family of linear inverse estimators which are derived from different priors on the signal regularity. Yang et al use local gradient features to propose an interpolation method which preserves edge sharpness [10].

II. PROPOSED METHOD

A. Proposed Method Block diagram:

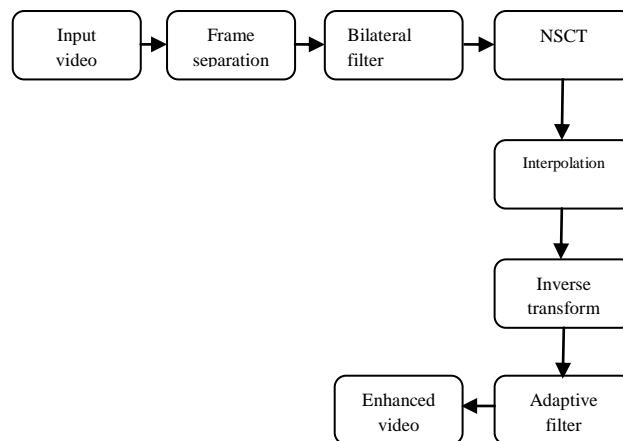


Fig.1 block diagram of proposed method

1. Bilateral Filter: The bilateral filter maintains edges by acting a mathematician convolution however attenuates the contributions of pixels by however totally different their intensities square measure from the intensity at the middle of the kernel. In Preprocessing of the proposed system the following steps namely Gray scale conversion, Noise removal is involved. In computing, a gray scale digital image has the value of each pixel is a single sample, it carries only intensity information. This sorted image, also known as black-and-white, is composed specially of shades of gray, varying from weakest intensity to strongest i. e. from black to white. Gray scale images are observed from one-bit bi-tonal black and white images with only the two colors i.e. black and Gray scale images have different shades of gray in between.

2. Non-Subsampled Contourlet Transform (NSCT): The non-subsampled Contourlet transform is a new kind of multi-scale and multi-directional transform that is recently developed on the base of Contourlet transform. It is absolutely shift invariance makes up the insufficiency of the subsampled Contourlet transformation proposed by Do and Vetterli. NSCT must be complete by the Pyramid scale decomposition and directional decomposition supported non subsampled directional filter banks.

Fig.1 shows the diagram of the NSCT and its band classification.

Shift-invariant version of CT having some excellent properties including both multilevel and multidirectional properties is NSCT [1]. NSCT able to design better representation of contours. Laplacian pyramid for multiscale decomposition and the DFB for directional decomposition is employed by CT. Reduction in the frequency aliasing of CT and to reach the shift invariance, down samplers and the up samplers are eliminated by NSCT during decomposition and reconstruction of image; that is designed on non-subsampled pyramid filter banks (NSPFBs) and the non-subsampled DFBs (NSDFBs).

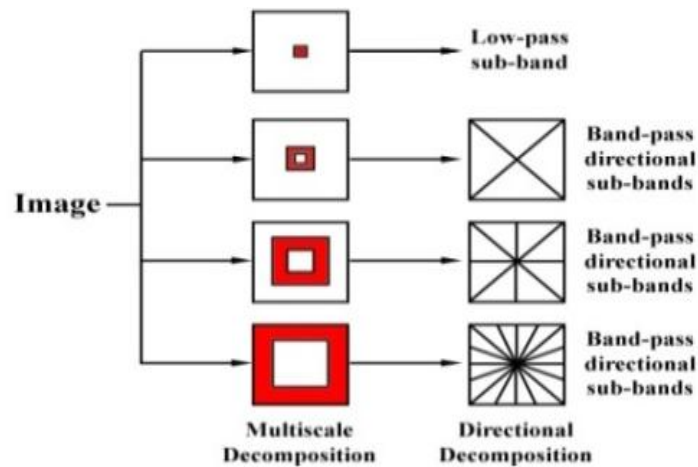


Fig 2 Non-subsampled Contourlet Transform

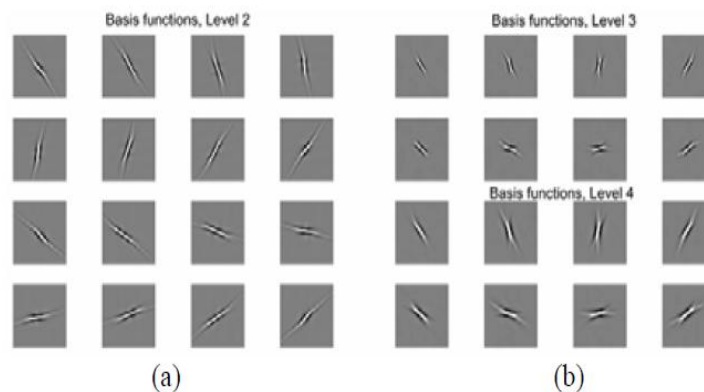


Fig3. Basis functions of the non-subsampled contourlet transform. (a) Basis functions of the second stage of the pyramid, (b) Basis functions of third (top 8) and fourth (bottom 8) stages of the pyramid.

Firstly, each level gets the low pass and band pass parts by steerable pyramid decomposition, then the band-pass part get the orientation information by directional filter banks, and the low-pass part works as the input of the next decomposition level. NSCT is a kind of multi-scale geometric analysis method with high redundancy. The NSCT coefficients correlated with useful information are represented as sparse distribution in each sub-band. Meanwhile, NSCT employs the anisotropic Contourlet-base as the basic decomposition unit of image, so it is multi-direction selectively, and each sub-band gives the detail information of image in one direction. Generally speaking, utilizing the anisotropic contourlet basis, the NSCT has the advantage of representing the singularity information of the image. In this aspect, it is better than NSWT with wavelet basis. And also, NSCT is of shift invariance, so it gives better performance than the down-sampled contourlet transformation. The following figure shows the NSCT basis function with different orientations in the design of directional filter banks. From Fig. 2, we can see the multi-directional characteristic of non-subsampled Contourlet basis function. And Fig. 3 shows the NSCT decomposition results of "peppers" image which is decomposed into four scales with four sub-bands in each scale(low frequency sub-band is omitted).

As can be seen from Fig. 2, the singularity features of the original image obtained a fine-to-coarse presentation in the four directional sub-bands respectively. Moreover, there are just few coefficients of speckle noise in scale $j=4$, and most coefficients in sub-bands of the finest scale are corresponding to useful information of the image. Similar with non-subsampled wavelet transform (NSWT), NSCT is also a multi-scale transform with translational invariance, but the sub-bands of NSCT have two distinct characteristics:

- (1) A high degree of redundancy: the coefficients of NSCT related to the useful information of the image present a sparse distribution in the finer scale.
- (2) NSCT uses anisotropic Contourlet basis, and the sub-bands in finer scales can capture details in different directions. And thus NSCT contains the character of multi-directional selectivity.

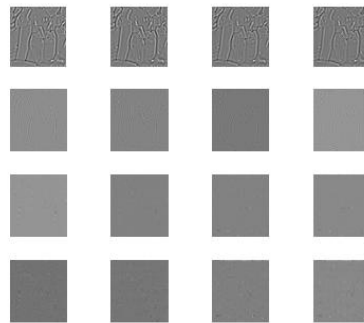


Fig4 Decomposition result of “peppers” image using NSCT.

3. Bicubic Interpolation: Bi-cubic interpolation is an extension of cubic interpolation for interpolating data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bi-cubic interpolation can be accomplished using either Lagrange polynomials, cubic splines, or cubic convolution algorithm. In image processing, bi-cubic interpolation is often chosen over bi-linear interpolation or nearest neighbor in image resampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels (2×2) into account, bi-cubic interpolation considers 16 pixels (4×4). Images resampled with bi-cubic interpolation are smoother and have fewer interpolation artifacts. This procedure yields a surface $p(x,y)$ on the unit sq. that is continuous and with continuous derivatives. Bi-cubic interpolation on associate at random sized regular grid will then be accomplished by repair along such bi-cubic surfaces, guaranteeing that the derivatives match on the boundaries

For Bi-cubic Interpolation (cubic convolution interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function is 16, two grid points on either side of the point under consideration for both horizontal and vertical directions. The grid points needed in one-dimension and two-dimension cubic convolution interpolation. For two-dimensional interpolation, the one-dimensional interpolation function is applied in both directions. It is a separable extension of the one-dimensional interpolation function.

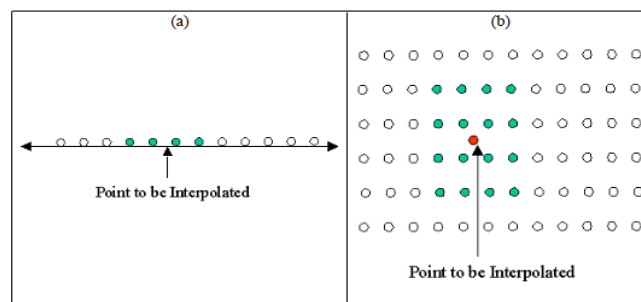


Fig 6. Grid points need in (a) one-dimension and (b) two-dimension cubic convolution interpolation

4. Adaptive Filter: The adaptive filter method consists of three important parts: (a) luminance image and background image, (b) adaptive adjustment, (c) color restoration. Firstly, Using color space conversion we will obtain the luminance image and background image, and afterwards adaptively managing the luminance image. The intensity limits can identify at one time is minimum, so the High Dynamic Range image is compressed. Contrast enhancement can modify important visual details so that we can get an image with better visibility

III. RESULTS AND DISCUSSION

Non-Subsampled Contourlet Transform (NSCT) for Gray scale video		
Sr.No	Parameter Names	Value
1	Processing time of Bilateral filter	6.380369
2	PSNR	25.04559
3	Entropy	7.69419
4	Mean	130.3583
5	Standard deviation	68.17907



Fig 6. (a) Input video frame



Fig 6. (b) Output video frame

Non-Subsampled Contourlet Transform (NSCT) for Colour video		
Sr. No	Parameter Names	Value
1	Processing time of Bilateral filter	8.85264
2	PSNR	28.78401
3	Entropy	7.711188
4	Mean	151.6153
5	Standard deviation	72.2094

Using contourlet transform we get PSNR value is 23.07, contourlet transform is existing method and using Non subsample contourlet transform we get PSNR 28.78, this is used in our paper. Non subsample contourlet transform better PSNR value than contourlet transform.

CONCLUSION

In this paper, we have proposed completely shift-invariant non-subsampled Contourlet Transform for efficient video enhancement. This transform provides perfect reconstruction after modifying coefficient, faster implementation and also clearly distinguishes noise edges and weak edges. The primary goal of the non-subsampled contourlet construction was to obtain a sparse expansion for typical images that are piecewise smooth away from smooth contours. And adaptive filter considering color information instead of traditional filters in obtaining background image and utilizing color space conversion to get luminance image and restore color using a linear algorithm. This algorithm has better visibility, the details are clear, and the colors are vivid and natural.

REFERENCES

- [1]. S. Farsiu, M. D. Robinson, M. Elad, and P. Milanfar, "Fast and robust multi frame super resolution," IEEE Trans. on Image Processing, vol.13, no. 10, pp. 1327-1344, Oct. 2004.
- [2]. H. Stark and P. Oskoui, "High resolution image recovery from image plane arrays, using convex projections," Journal of Optical Society of America A, vol. 6, no. 11, pp. 1715-1726, 1989.
- [3]. M. Irani and S. Peleg, "Improving resolution by image registration, CVGIP: Graphical Models and Image Processing, vol. 53, no. 3, pp.231-239, 1991.
- [4]. X. Li and M. T. Orchard, "New Edge Directed Interpolation," IEEE Trans. on Signal Processing, vol. 10, no. 10, pp.1521-1527, 2001.
- [5]. S. Farsiu, M. D. Robinson, M. Elad, and P. Milanfar, "Fast and robust multi frame super resolution," IEEE Trans. on Image Processing, vol.13, no. 10, pp. 1327-1344, Oct. 2004.
- [6]. X. Zhang, X. Wu, "Image interpolation by adaptive 2D auto regressive modeling and soft-decision estimation," IEEE Trans. on Image Processing, vol. 17, no. 6, pp. 887-896, 2008.
- [7]. X. Li and M. T. Orchard, "New Edge Directed Interpolation," IEEE Trans. on Signal Processing, vol. 10, no. 10, pp.1521-1527, 2001.
- [8]. Zahra Ashouri, Student Member, Shahram Shirani, Senior Member, IEEE "Video Super Resolution Using Contourlet Transform and Bilateral Total Variation Filter" IEEE Transactions on Consumer Electronics, Vol. 59, No. 3, August 2013