A REGULARIZED ROBUST SUPER-RESOLUTION APPROACH FORALIASED IMAGES AND LOW RESOLUTION VIDEOS

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ABSTRACT

This paper presents a hybrid approach for images and video super-resolution. We have proposed the approach for enhancing the resolution of images and low resolution, under sampled videos. We exploited the shift and motion based robust super-resolution (SR)algorithm [1] and the diffusion image regularization method proposed in [2] to obtain the alias free and jerk free smooth SR image.We presented a framework for obtaining super-resolution video thatis robust,even in the presence of fast changing video frames. Wecompare our hybrid approach framework's simulation results with different resolution enhancement techniques i.e. Robust Super-resolution, IBP and Interpolation methods reported in the literature. This approach shows good results in term of different quality parameters.

KEYWORDS

Super-resolution, Motion estimation, Regularization

1. INTRODUCTION

Image super-resolution is the most widely and extensive areaof research for decades[3] to solve the problem of limited resolution by image acquisitiondevices.It has wide applications in video surveillance, remote imaging,medical imaging etc. Resolution enhancement or super-resolution is the process of obtaining high resolution images from one or more LR images. Super-resolution has been applied primarily to spatial and temporal resolution enhancement.Increasing the resolution of image sensor is one way of increasing the resolution of the acquired images. This solution, however, may not be feasible due to the increased associated cost of imaging devices and the fact that shot noiseincreases during acquisition as the pixel size becomes smaller.Furthermore, increasing the chip size to accommodate the larger number of pixels increases the capacitance, which in turn reduces the data transfer rate.

Methods for super-resolution can be generally be categorised in two ways: (1) Multi imagesbased super resolution, (2) Single image based super resolution or example based super resolution. In the Multi imagesbased SR, a few set of low resolution images of the same scene are taken. Each low resolution image isavailable with some motion and shift (sub pixel shift). By image registration, a high resolution image is obtained. There are fourmain classes of methods to estimate the pixel values in super-resolution grid. These methods are namely,frequency domain approaches, learning based approaches[4, 5], iterativeSR image reconstruction techniques [6, 7]and interpolation-basedapproaches [8, 9].In recent years very large numbers of techniques and methods have been proposed for image up-scaling.The goal of these methods is to magnify (up-

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scale)an image while maintaining the image fidelity and maintaining the edges and details of the images.

In recent years a robustsuper-resolution and iterative backpropagation SR methods have been implemented by different authors. The multi-frame resolution enhancement problem was addressedfirst in[10], where frequency domain approach has been proposed. The images taken by low resolution devices with small CCD resulting small noisy frames generally blurred by both atmospheric turbulence, camera lens and by PSF of LR sensor.The general model to represent the LR image formation can be mathematically defined as follows [11]:

$$y(m,n)=\{A_{atmos}(x,y)\otimes W(C_{camera}(x,y)\otimes I(x,y))\}\downarrow+N(m,n) \tag{1}$$

Where $\otimes$ is 2D convolution operator, W is the warping operator, $\downarrow$ is the discretising operator, $N(m,n)$ is the system noise and $y(m,n)$ is the resulting noisy and blurred image. Fig.1 elaborates the mathematical equation (1).

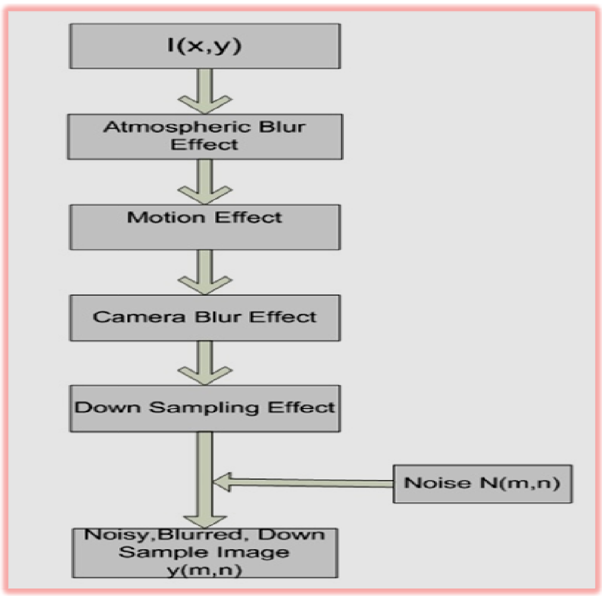


Fig.1. Noisy Image Formation Model

In this paper, we use and exploit the advantages of Patrick Vandewalle'smotion estimation based robust super-resolution algorithm [1] andthe method proposed by Penona& Malik[2] based on regularization technique for obtaining better fidelity of images. We use these techniques for our proposed algorithm and applied it to video SR. We adapted existing SR enhancement techniqueand motion estimation technique along with image regularization in obtaining super-resolution images and videos. We usemotion estimation prior to robust image super-resolution techniques followed by Perona& Malik image diffusion algorithm to obtain super-resolution images which gives much better results in quality in term of images parameter i.e. PSNR, SNR etc.

The remainder of this paper is organised in the following way. Section 2illustrates existing SR approaches. Section 3 elaborateslinear motion estimation algorithm, where shift and rotation parameterare estimated.These estimated valuesare used in the SR method. Section 4describes Perona& Malik [2]diffusion regularization algorithm. Our hybrid proposed methodology for images and videos has been presented in Section 5. Section 6presents experimental results & qualitative analysis of images and videos results.Section 7 concludes the paper.

2. RESOLUTION ENHANCEMENT ALGORITHMS

2.1 Robust Image Super resolution

Robust SRapproach proposed by AssafZomet et al. [12] is robust to outliers caused by model inaccuracies and fast moving object. It introduced robustness in the procedure by replacing the sum of images with a scaled pixel wise median. It is observed that, in case of the present of distant outliers the median is much more robust than mean. The importance of pixel wise median can be justified with the minimization of error under different norm which can handle outliers better than the l norm.

2.2 Iterative back propagation Super resolution

Irani et al. [13, 14, 15, 16]formulated the iterative back propagation approach. In this method the SR image is estimated by back projecting the error/difference between artificially LR image and observed LR images. This process is repeated again and again to minimize the error. A mathematical model of the iterative back projection algorithm is:

$$\hat{I}^{n+1} = \hat{I}^{n} - \lambda \sum_{i=1}^{P} H_i^{BP} (\hat{g}_i^{n} - g_i) \tag{2}$$

Where $\hat{I}^{n+1}$ is the SR image gained in $(n+1)'th$ iteration, n is the iteration number, $\hat{I}^{n}$ is the SR image obtained in the n^th^ iteration , H_i^{BP} is the $i'th$ back projection operation, $\hat{g}_i^{n}$ is the $i'th$ LR image of $\hat{I}^{n}$ under the LR image observation model and finally λ is the gradient step.

2.3 Image Interpolation

Interpolation based methods basically treat resolution enhancement as a non-uniform interpolation problem. It is generally computationally efficient due to the nature of manipulating the image matrix in spatial domain. Symmetric, bicubic and bilinear image interpolation methods can be employed in the obtaining the high resolution images. It is generally proved to be fastest but produces the some blurring in image so need regularization techniques to denoiseimages after interpolation. There are various implementations of interpolation techniques addressed by [17, 18, 19].

3. IMAGE LINEAR MOTION ESTIMATION

Patrick Vandewalle[1] uses the property that a shift in the space domain is translated into a linear shift in the phase of the image's Fourier transform. Similarly, a rotation in the space domain is visible in the amplitude of the Fourier Transform. Hence, Vandewalleet.al. motion estimation algorithm computes the image'sFourier transforms and determines the 1-D shifts in both their amplitudes and phases.

One advantage of this method is that it discards high-frequency components, where aliasing may have occurred, in order to be more robust. This algorithm uses the information from subpixel shifted LR images which is down-sampled. The estimation of the displacement (or velocity) of image structures from one frame to another in a time-sequence of 2-D images is regards as motion estimation. The 2-D displacement of the pixel located at point p in one frame at time t to consecutive frame at time $t+\Delta t$. Figure 2 shows the pixel motion.

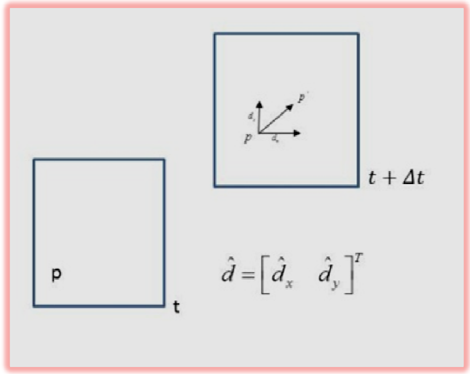


Fig.2 Pixel Motion in co-ordinates

The motion between two images will be a function of three continuous variable parameters:horizontal shift, vertical shift and a planar rotation angle ϕ.Estimation of horizontal shift Δx_1 and vertical shift Δx_2 can be easily calculated in frequency domain. Assume the reference signal $f_1(x)$ and shifted and rotated signal $f_2(x)$:

$$f_2(x) = f_1(R(x+\Delta x)) \tag{3}$$

Where $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$, $\Delta x = \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \end{bmatrix}$, $R = \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix}$

It can be expressed in FT as follows:

$$F_2(u) = \iint_x f_2(x) e^{-j2\pi u^T x} dx$$

$$= e^{j2\pi u^T \Delta x} \iint_{x'} f_1(Rx') e^{-j2\pi u^T x'} dx' \tag{4}$$

With $F_2(u)$, the Fouriertransforms of $f_2(x)$ and the co-ordinate transform $x' = x + \Delta x$ .After another transformation $x'' = Rx'$, the relation between the amplitudes of the Fourier transform can be computed as:

$$|F_2(u)| = \left| e^{j2\pi u^T \Delta x} \iint_{x'} f_1(Rx') e^{-j2\pi u^T x'} dx' \right| \tag{5}$$

$$= \left| \iint_x f_1(x'') e^{-j2\pi u^T (R^T x'')} dx'' \right|$$

$$= |F_1(Ru)|.$$

$|F_2(Ru)|$ is the rotated version of $|F_1(Ru)|$ over the same angle ϕ . The estimation of rotation angle ϕ can be calculated from the amplitudes of the Fourier transform of $|F_1(Ru)|$, $|F_2(Ru)|$. A shift of the image parallel to the image plane can be expressed in Fourier domain as a linear phase shift

$$F_2(u) = \iint_x f_2(x)e^{-j2\pi u^T x}dx = \iint_x f_1(x+\Delta x)e^{-j2\pi u^T s}dx \tag{6}$$

The shift parameter Δx can be computed as the slope of phase difference $\angle(F_2(u))/F_1(u))$.

4. ANISOTROPIC DIFFUSION REGULARIZATION

Anisotropic diffusion has been first proposed by Perona and Malik [2] and it is a useful tool for multiscale description of images i.e. Edge detection image regularization, image enhancement and image segmentation.The diffusion should be chosen in such a way that there will be more diffusion in smooth area and less around large intensity transition so that small variations in image intensity i.e. noise and unwanted texture, are smoothed and the edges are preserved. It diffuses around large intensity transition to sharp the edges and forward diffuse in smooth areas for noise removal.

The initial image is convolving with Gaussiankernel prior to the calculation of the gradient in all direction. In the case of linear diffusion the gradient is calculated in all direction in a linear fashion. 2-D anisotropic diffusion. Linear diffusion has been used in this paper for the image regularization in the post process step. Inthe recent years various diffusion with edge preserving nature has been implemented in [20, 21, 22].

5. Proposed approach

5.1 Propose SR Image Methodology

We have developed a hybrid approach of SR reconstructionthat exploits the advantages of motion estimation algorithm, robust SR and regularization. Firstly, weestimate motion between shifted and rotated LR frames with Vandewille motion estimation algorithm. Then we applied robust super-resolutionapproach for obtaining the HR images. Thereafter, Perona& Malik image regularization is performedon obtained HR image to obtain Final SR image that shows good image fidelity. The Figure.3 illustrates the approach.

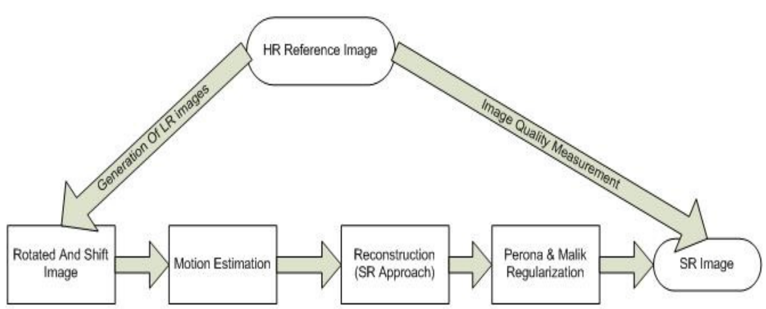


Fig.3 Generation of Artificial shifted and alias Image for Combined approach Estimation of motion

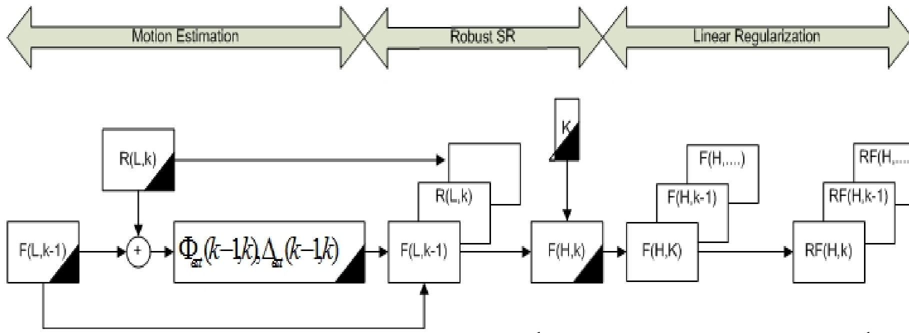


Fig. 4 Elaborating SR video Approach where R(L, k) is kth LR frame and F(L,k-1) is (k-1)th LR frame. F(H, k) is kth HR frame. RF(H,k) is Regularized frame of F(L,k). K is the interpolation factor

5.2 METHODOLOGY FOR VIDEO SUPER RESOLUTION

A high resolution video contains the sequence of frames. $f_{HR,m}\ m=(0,1,.......,M-1)$ reconstructed from a sequence of low resolution video frames $f_{LR,m}\ m=(0,1,........,M-1)$ by our hybrid approach. Figure.4 elaborates the video SR approach. The steps of algorithms are as follows:

1. The LR video's each frame is extracted and converted images. We can store these images. We will use these LR image frames inthe algorithm.

2. We take Two of these LR image in sequence at a time for the estimation of motion parameters.

3. ***Motion Estimation:*** Shifts and rotation are estimated by using the algorithm by Vandewalleet.al. in frequency domain.
   a. ***Rotation Estimation:***Linear motion Estimation is used in the estimation of shift angle between the reference frame and the next frames.
   b. ***Shift Estimation:*** we calculate the vertical and horizontal shift between the reference frame and the next frame.

4. ***Robust Super-resolution:***A HR frame f_{HR} is reconstructed from the set of two continuous registered frames. Given interpolation factor is k.
   a. Shift and rotation angle parameter will be used to get HR frames.
   b. By using the calculated parameters values Robust SR algorithms for two LR frames to get the HR frames.

5. Step 1 to step 4similar is repeated for all LR frames/image of video to get corresponding HR images.

6. ***Regularization:***Linear diffusion on each SR image obtained is performed to get the linearly diffused regularized image with Gaussian kernel size 5×5 .
   a. Each SR image is dissolved into individual planes and linear diffusion is performed on each plane of the SR images frames.
   b. Combing all regularized planes into respective frames.
   c. Similar Approach of diffusion is performed on each frames of the video to get SR regularized image.

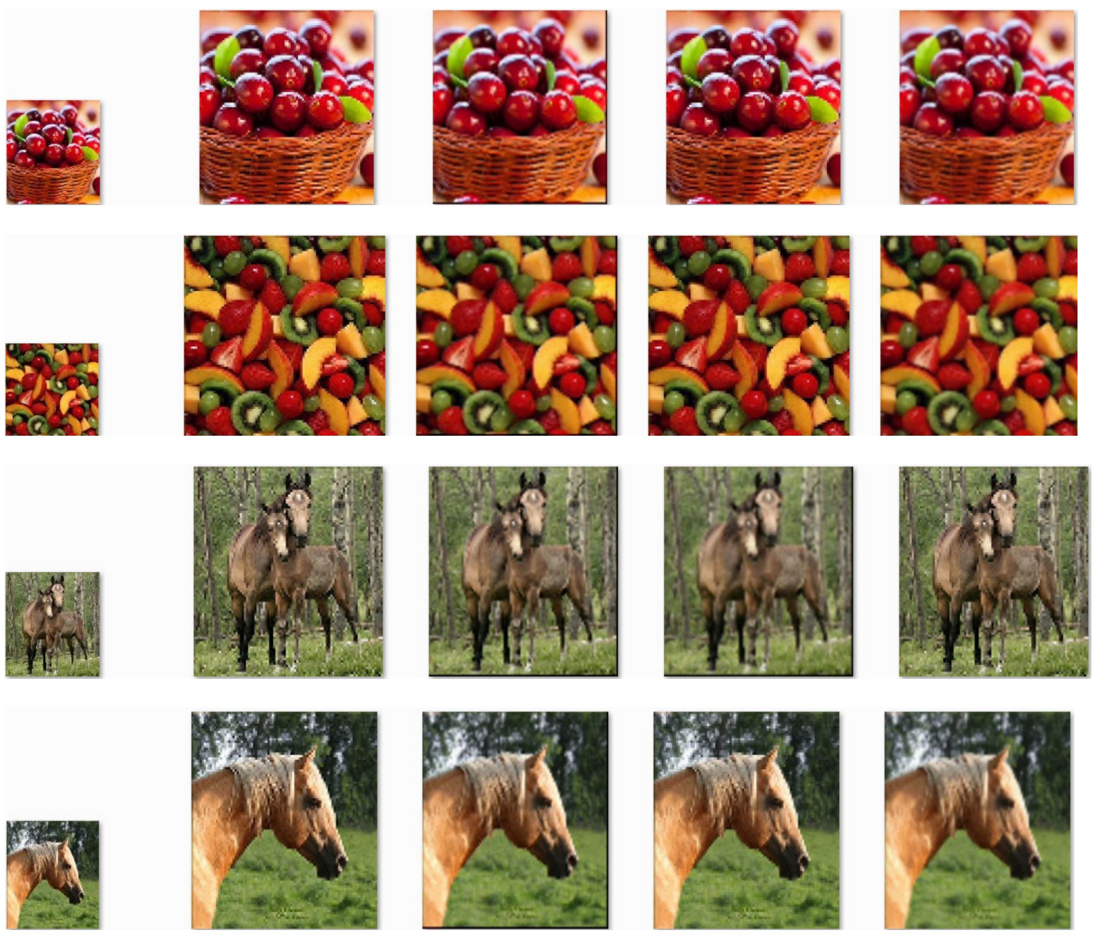
7. Now, all HR frames are combined to get SR video.

6. EXPERIMENTAL RESULTS & QUALITATIVE ANALYSIS

In the calculation of image/video quality measurement parameter, we will use five different mathematically defined metrics i.e.PSNR, MAE, Measure of improvement (EME)[23] of original image and restored image, Universal image quality index(Q) [24].The dynamic range of Q is [-1, 1]. Higher PSNRvalue indicates the reconstruction is of higher quality. EME of original images and restored images respectively is calculated. Higher the EME_noisyvalues show good image fidelity with respect to EME_ori.We tested our SR scheme on artificially generated shifted and rotated image as well as images from the web. We have performed our simulation and calculated results on MATLAB R2009a. We compared our results with three different algorithmsi.e.Griddata function using bicubic interpolation, Iterative Back propagation approach, Robust SR.

6.1 Experimental Results of Images

We have taken five different HR image of resolution 360×360 . Then generated shifted and rotated LR version of images of size 90×90 , by adding randomly generated shift matrix and rotation matrix. Then we generated HR imagesfrom generated LR image by a factor of 4 from different SR approach. Then compared the our hybrid approach with existing SR approach presented in Table 1,2,3,4 based onQuality parameter value i.e. PSNR, Q, SNR, EME of original images and restored images respective. Fig 5 shows the results on images.



(a)	(b)	(c)	(d)	(e)
90×90	360×360	360×360	360×360	360×360
LR Image	IBP	Interpolation	Robust SR	Proposed

Fig. 5 Images results of three SR algorithm and our approach with SR factor k=4

	PSNR	Q	EME_ORI	EME_NOISY	SNR
Fruits	22.471	.674658	18.6683	15.704	-1.698
Mix fruit	21.4897	0.805276	20.6955	18.9221	-2.692
Horse1	23.9665	.731062	23.3618	18.334	-.2726
Horse2	21.0976	.595922	19.1654	13.3726	-3.059
Lichi	23.0119	.750352	12.8502	10.9815	-1.088

Table.1 Qualitative image parameters values using interpolation

	PSNR	Q	EME_ORI	EME_NOISY	SNR
Fruits	19.3248	.408736	18.6683	14.0912	-4.8446
Mix fruit	18.5029	.525034	20.6955	17.2157	-5.679
Horse1	21.5936	.49499	23.3618	15.0307	-2.646
Horse2	18.6316	.331147	19.1654	13.5207	-5.526
Lichi	20.814	.457958	12.8502	11.2937	-3.287

Table.2 Qualitative image parameters values using IBP

	PSNR	Q	EME_ORI	EME_NOISY	SNR
Fruits	20.2473	.43946	18.6683	11.2847	-3.922
Mix fruit	18.9173	.53643	20.6955	14.770	-5.265
Horse1	22..121	.518001	23.3618	13.2182	-2.227
Horse2	19.6187	.35364	19.1654	11.0459	-4.538
Lichi	21.833	.4898	12.8502	7.85821	-2.267

Table.3 Qualitative image parameters values using robust super-resolution

	PSNR	Q	EME_ORI	EME_NOISY	SNR
Fruits	22.3315	.527406	18.6683	11.2988	-1.8379
Mix fruit	21.586	.652167	20.6955	13.9831	-2.5960
Horse1	24.2371	.630459	23.3618	14.507	-.00214
Horse2	21.818	.427115	19.1654	10.5061	-2.3392
Lichi	23.8586	.577265	12.8502	8.445	-.24199

Table.4 Qualitative image parameter values using hybrid approach

6.2 Simulation results of Videos

We have taken eight set of HR video set1, set2…set8 of different resolution of different degradation levels. Each HR video is of 99 frames and the frame rate of 15 fps. Theoriginal video is taken from YouTube. Each original video‘s LR sample has been generated frame by frame using Matlab built-in resize function. These sample videos contain both large scale local motion and relatively small background global motion.SR video is generated by above three mentioned SR algorithms and our approach.

We have calculated the average values of parameter. The comparative analysis is presented in Table 5,6, 7, 8 and Fig 7 Where R is original HR video resolution and K is the factor by which LR videos have been generated.

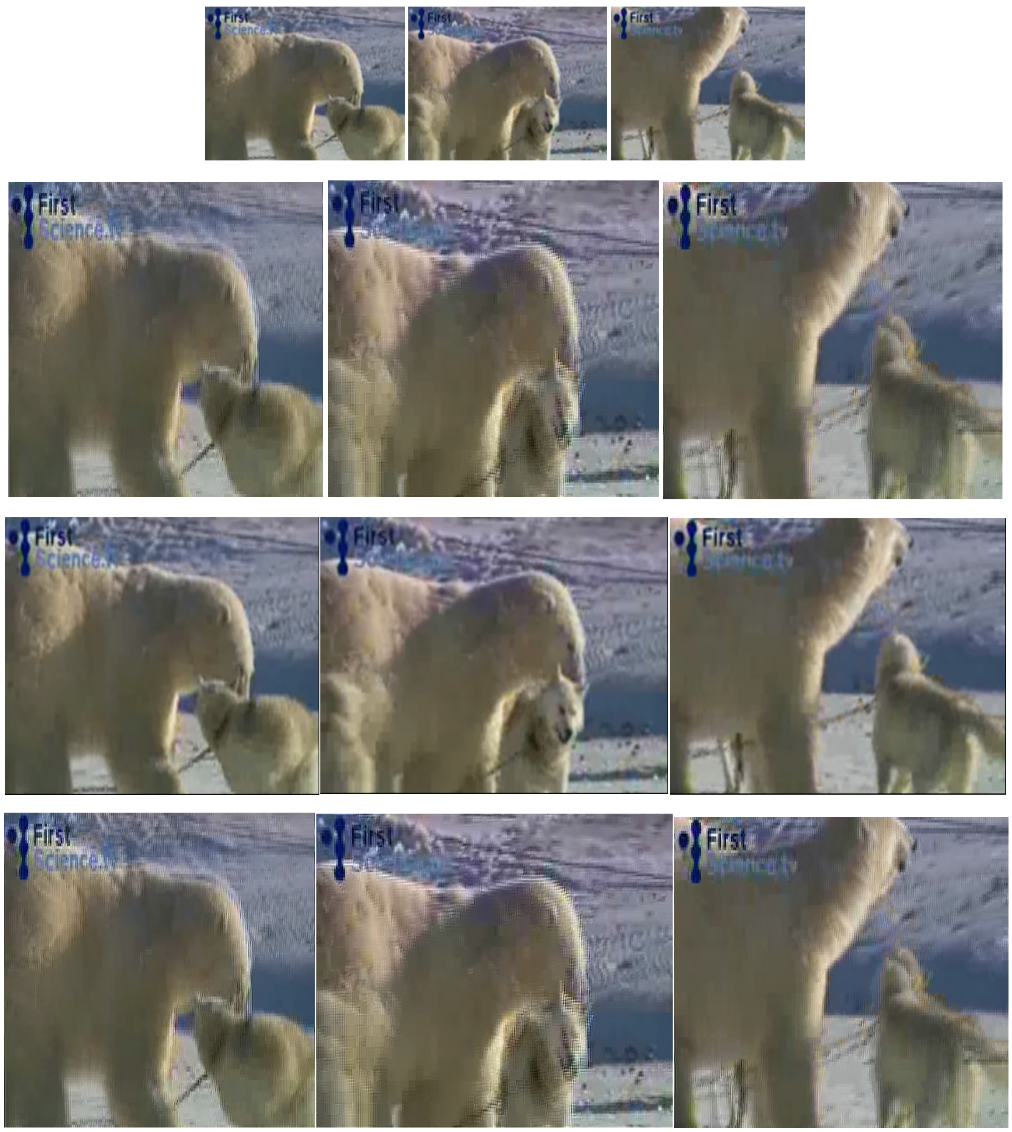


Fig. 6 20th,28th,36th LR sample frame of sample1of size 200-by-113 and corresponding HR video of size 400-by-226, 1st Row: Input LR video frames, 2nd Row: Video frames by RS, 3rd Row: Video frames by Inperpolation, 4th Row: video frames by IBP, 5th Row: Our approach.

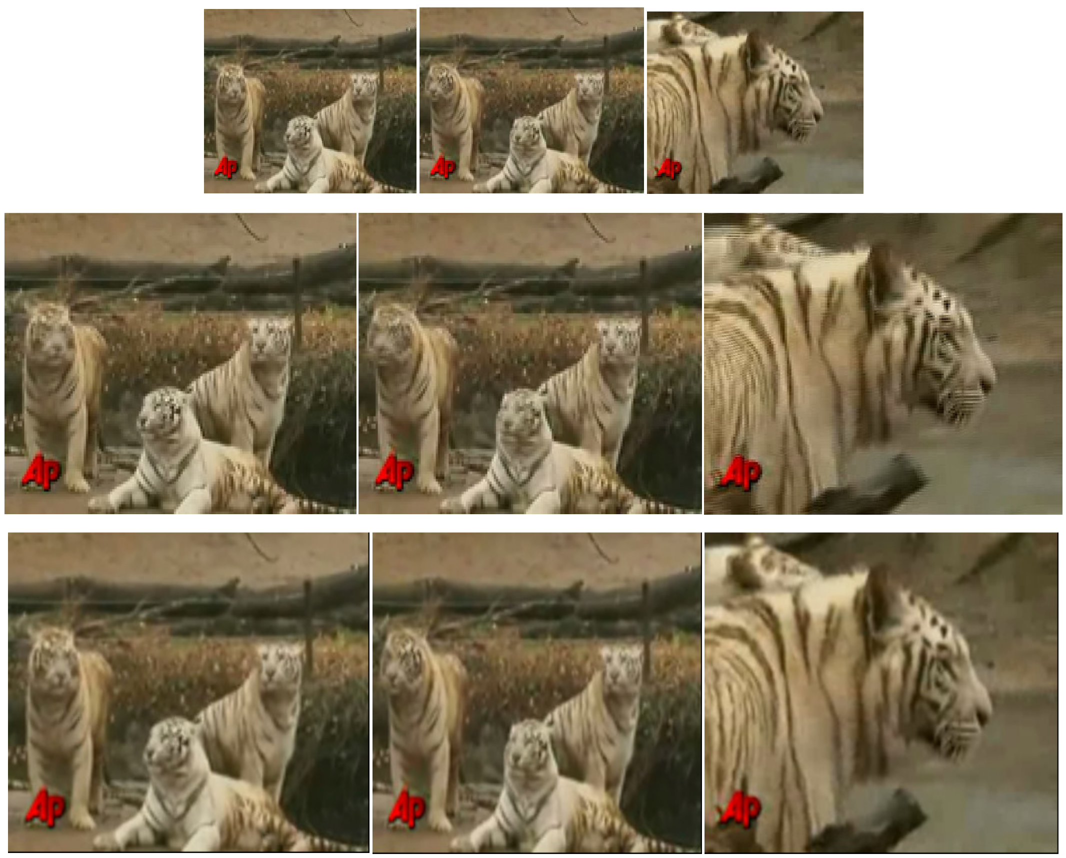


Fig. 7 20th,28th,36th LR sample frame of sample3of size 160-by-120 and corresponding HR video of size 320-by-240, 1st Row: Input LR video frames, 2nd Row: Video frames by RS, 3rd Row: Video frames by Inperpolation, 4th Row: video frames by IBP, 5th Row: Our approach.

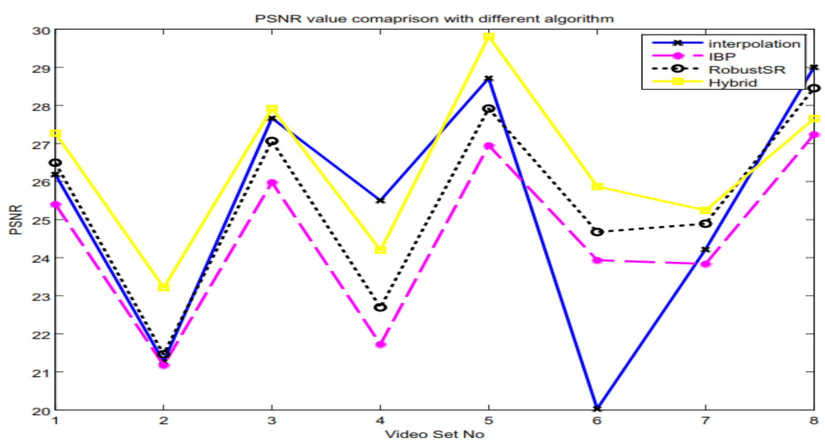


Fig. 8 Plot of PSNR value of video samples

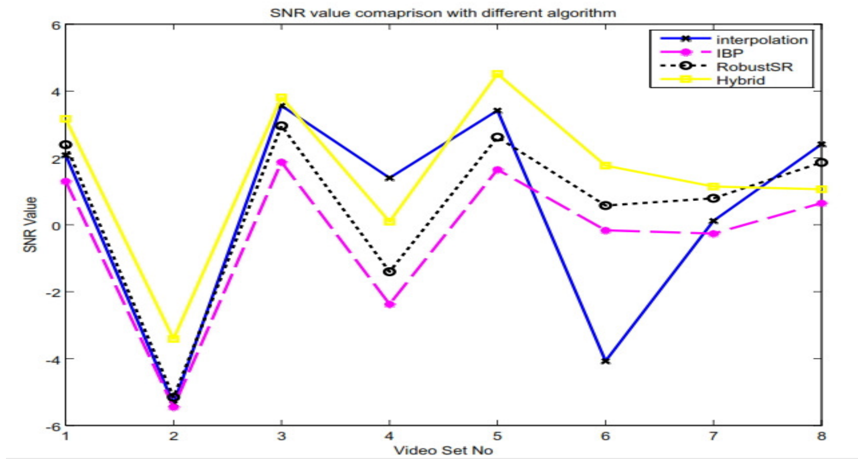


Fig. 9 Plot of SNR value of video samples

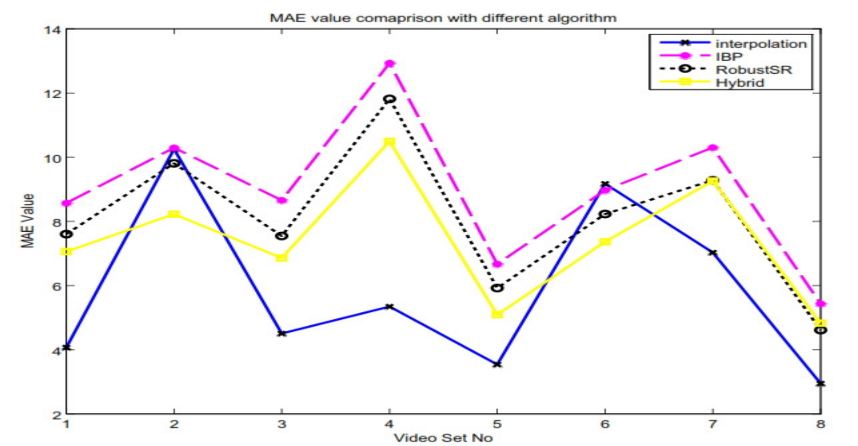


Fig. 10 Plot of MAE value of video samples

8. CONCLUSION

In this paper, we present a hybrid approach for video super-resolution for alias and shifted images.Hybrid approach uses the vandewalle motion estimation with robustsuper-resolution followed by diffusion regularization. We compare our approach results with Griddata interpolation,IBP,and Robust SR method in terms of different parameters value. Experimental results of image and video prove the improvement over existing algorithm. There is significant improvement in the value of all the parameter. We have applied the algorithm on videos and imagesupto resolution factor 4. The comparative analysis done on the basis of data collected in Tables mentioned. So our approaches improve video super resolution by motion estimated robustsuper resolution with linear regularization.

REFERENCES

[1] Patrick Vandewalleet. al., "A Frequency Domain Approach to Registration ofAliased Images with Application to Super-resolution,"*EURASIP Journal on Applied Signal Processing*, 2006.

[2] P. Perona, J. Malik, "Scale space and edge detection using anisotropic diffusion," in *Proc. IEEE Computer Society Workshop on Computer Vision*, Washington, pp. 16–22, 1987.

[3] S. Borman, R.L. Stevenson, "Super-resolution from image sequences-A review," in *Proc. 1998 Midwest Symp. Circuits and Systems,* pp. 374-378, 1999.

[4] W. T. Freeman and E. C. Pasztor, "Learning low-level vision," in *Proc.IEEE Int. Conf. Computer Vision*, pp. 1182–1189, 1999.

[5] W. T. Freeman, T. R. Jones and E. C. Pasztor, "Example-based super-resolution," *IEEE Comput. Graph.*Appl., vol. 22, no. 2, pp. 56–65, Mar 2002.

[6] Wan, Lin Meng, Dong Ming, Hongzhi Qi, Yong Hu, Luk, K.D.K, "Video image super-resolution restoration based on iterative back-projection algorithm," *IEEE International Conference on Computational Intelligence for Measurement Systems and Applications*, pp. 46- 49, May. 2009.

[7] Xiuju Liang, ZongliangGan, "An Effective Iterative Back Projection Based Single Image Super Resolution Approach," in *Sixth International Conference on Image and Graphics*, pp. 176-181, 2011.

[8] L. Xin and M. T. Orchard, "New edge-directed interpolation," *IEEE Trans. Image Processing*, vol. 10, no. 10, pp. 1521–1527, Oct. 2001.

[9] Z. Xiong, X. Sun, and F. Wu, "Fast directional image interpolator withdifference projection," in *Proc. IEEE Int. Conf. Multimedia & Expo*, 2009, pp. 81–84.

[10] T. S. Huang and R. Y. Tsai, "Multi-frame image restoration and registration," *Adv. Comput. Vis. Image Process*., vol. 1, pp. 317–339, 1984.

[11] SinaFarsiu, M. Dirk Robinson, "Fast and Robust Multiframe Super Resolution," in *IEEE Transactions on Image Processing*, vol. 13, October 2004.

[12] A. Zomet, A. Rav-Acha, and S. Peleg, "Robust super resolution," in *Proc. Int. Conf. Computer Vision and Patern Recognition*, vol. 1, pp. 645–650, Dec.2001.

[13] Irani M, Peleg S., "Improving resolution by image registration," in *CVGIP, Graph Models Image Process.*, pp. 231-239, 1991.

[14] CAO Ju-liang, LU Hai-bao, TAN Xiao-bo, ZHOU Wei-hong, "Super-resolution of image sequences based on real-time frame iterative back projection algorithm," *Optical Technique*. 2004.

[15] Qin F-Q, He X-H, Chen W-L, Yang X-M, Wu W, "Video superresolution reconstruction based on sub-pixel registration and iterative backprojection," *Journal of Electronic Imaging*, 2009.

[16] Haiying Song, Xiaohai He, Weilong Chen, Yanyue Sun, "An Improved Iterative Back-Projection Algorithm for Video Super-Resolution Reconstruction," in *Photonics and Optoelectronic (SOPO)*, pp. 1- 4, 2010.

[17] Fei Zhou, Wenming Yang, Qingmin Liao, "Interpolation-Based Image Super-Resolution Using Multisurface Fitting," in *IEEE Transactions on Image Processing*, vol. 21, pp. 3312-3318, 2012.

[18] Yallapurmath, Vanishree, Kurian, M. Z., Guruprasad, H. S., "Design and implementation of interpolation algorithms for image super resolution," in *8th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP)*, pp. 1-6, 2012.

[19] Kwok-Wai Hung, Wan-Chi Siu, "Single image super-resolution using iterative Wiener filter," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1269-1272, 2012.

[20] Shin-Min Chao, Du-Ming Tsai, Wei-Yao Chiu, Wei-Chen Li, "Anisotropic diffusion-based detail-preserving smoothing for image restoration," in *IEEE International Conference on Image Processing (ICIP)*, pp. 4145-4148, 2010.

[21] Wang Zhiming, Bao Hong, Zhang Li, "Anisotropic diffusion based on directional consistency," in *IEEE International Conference on Intelligent Computing and Intelligent Systems (ICIS)*, vol. 1, pp. 521-525, 2010.

[22] Lavialle, Olivier, Germain, Christian, Borda, Monica E., "Asymmetric anisotropic diffusion," in *IEEE International Conference onImage Processing (ICIP)*, pp. 3889-3892, 2009.

[23] Os S. Agaian et al. "A New Measure of Image Enhancement," *IASTED International Conference on Signal Processing & Communication*, 2000.

[24] Zhou Wang and Alan C. Bovik, "A Universal Image Quality Index," in *IEEE Signal Processing Letters*, vol. 9, pp. 81-84, March 2002.

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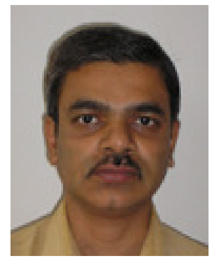

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