VIDEO SUPER RESOLUTION RECONSTRUCTION FROM LOW RESOLUTION IMAGES USING SPLINE INTERPOLATION

[1]V. VENUBABU, [2]M. V. RAGHUNADH

Department of E and CE, NIT Warangal, India
Email: venu.vemparala@gmail.com, raghunadhmv@gmail.com

Abstract—Transmitting a real time video for Military, Satellite, Cellular and Surveillance applications over a low bandwidth channel is a challenging problem. Due to limited channel bandwidth, the bit rate of high resolution image/video is decreased by decimation (down sampling) and transmitted through the channel, resulting in a low bit rate compressed image. At the output(receiving) side, the high resolution image/video is reconstructed from the set of compressed low resolution noisy and blurred images using a technique known as super resolution. In this paper we explain the problem of reconstructing a high resolution image/video using several low bit rate compressed (low resolution) noisy and blurred images is considered. We propose an efficient method for reconstruction of a high resolution image using a set of low resolution images, Spline interpolation and De-blurring. The performance of the proposed method is verified using objective and subjective quality measures for an image. Based on the experimental results, the proposed algorithm provides a better PSNR (Peak Signal to Noise Ratio), SSIM (structural similarity index measure) and SNR (Signal to Noise Ratio).

Keyword- Motion estimation, spline interpolation and super resolution (SR).

I. INTRODUCTION

Super Resolution Reconstruction (SRR) is one of the emerging technology used in Military, Satellite and Cellular applications. Due to low processing power of a system and low bandwidth capability of the channel, it is difficult to transmit a high resolution image through the channel. For efficient use of a low bandwidth channel compressed version of a high resolution images sent through the channel and at the receiving side the high resolution (HR) image can be reconstructed using a sequence of compressed low resolution (LR) images. Super Resolution (SR) is a process of increasing the number of pixels in an image for more details using a set of low resolution images. The spatial distance between the pixel decreases as number of pixels increases in an image using a low resolution images and possible to preserve a high frequency components such as edges and completely removing the degradations arises from the common imaging system [1] via down sampling, blur and noise. Each low resolution image captures a small amount of information from the scene; The main goal of super resolution is construction of a high resolution image from a squence of low resolutions images by extracting an unique information from each low resolution image. They are different methods for constructing the HR image, these methods are based on multiple low resolution images and a single low resolution image. Almost all the SR algorithms are based on the reconstruction of multiple low resolution images using the sub-pixel motion shifts and nonuniform to uniform sampling techniques.

The rest of the paper is organized as follows: The detailed literature survey is discussed in section II, mathematical formation model of super resolution is discussed in section III, and in section IV the proposed method is explained in detail. And then, the results and conclusions were discussed in section V, VI respectively.

II. LITERATURE SURVEY

To slove the problem of limited resolution devices the super resolution was studied from decades [2]. The main goal of super resolution is to reconstruct a high resolution image from a set of compressed low resolution images. They are different methods to construct a high resolution image and they are mainly classified as frequency domain approaches [3], learning based techniques [4], iterative reconstruction and interpolation based techniques [5], [6], [7] and dynamic tree and wavelet based resolution techniques [8]. Based on literature work [2], [9] considers the different super resolution techniques based on filtering approach in spatial domain. Early works on super resolution considers [10] transformation of non-uniform samples into uniform samples using the concept of the sampling theorem [11] with out loss of data by satisfying the Nyquist theorem. Some of the super resolution techniques are considered as frequency domain techniques for registering the images using the properties of the discrete Fourier transform [3] and this approach only considers the global rotation of the image and it is sensitive to noise. In [12] this an algorithm is proposed for effectively eliminating the blurring effect caused by sensor using the POCS (Projection of convex sets). This algorithm need an early knowledge of process constructions, it is slow convergence and the accuracy of HR image depends on initial guess of the algorithm. An Iterative Back Projection algorithm is proposed in [13] it iteratively decreases the reconstruction error between a low resolution image

and a high resolution image by converting a high resolution into a low resolution image using back projection. The constraints and priori knowledge of IBP (Iterative Back Projection) techniques is very difficult compared to [12].

Dynamic tree structure model SR(super resolution) is proposed in [14] with a mean field approach. In this algorithm the high resolution images is a combination of series of patches with different shapes. Due to different nature of priori and measured image this algorithm is producing erroneous results for some conditions. Learning based super resolution is proposed in [4] using an Adaptive Regularization. In this the high resolution image was reconstructed using a single low resolution image with pair matching. This algorithm requires large collection of database and storage space. [15] proposed an algorithm for video super resolution using the quality coefficients for an accurate motion estimation and number of LR frames required of this algorithm is 8 to 16. Super resolution using wavelet techniques is require more memory, this memory requirement can be decreased by using wavelet lifting schemes proposed in [8] using SPHIT. In this algorithm FFT based image registration technique is used and this method is sensitive to noise and it is work for only global rotation. Based on Kernel Regression and spatial temporal orientation a super resolution algorithm is proposed in [16] according to this method kernel regression is best way to use irregular interpolation and this method is causes a loss of edges and boarder information. Super resolution reconstruction is an inverse problem is effectively eliminated by regularization of an image is proposed in [17] with bilateral total variance. This algorithm suffers due to smooth output and loss of edges.

Using the higher order motion prediction and bilateral filtering a new super resolution algorithm is proposed in [18].

According this algorithm a high order prediction is used to find the sub pixel motion with structural similarity features. This algorithm is not suitable for aliased images due to loss of structure edges. The variable block size motion estimation algorithm for super resolution is proposed in [19] for decreasing the local and global error of an image up to sub pixel variations. The global level registration is present between a set of high resolution images. A multi-resolution analysis based super resolution approach is proposed in [20]. Multi resolution analysis is used to approximate edges with less coefficients compared to wavelet transform and this method suffers from an unwanted frequency components due to interpolation. The high resolution image constructed from correlation function and non local means is proposed in [5]. This is invariant to blur and resolution factor and it is an iterative algorithm. The image reconstruction algorithm using spline interpolation is proposed in [6], [7] using single image. Image interpolation using single image basically produce smooth results and loss of high frequency components such as edges and human eye is more sensitive edges. The proposed algorithm reconstruct a high resolution image using a set of sub-pixel shifted low resolution images and each sub-pixel shifted image contains different information after combining each low resolution image the high resolution image provides more details than any of the interpolated single image. The high resolution image can be constructed using multiple low resolution images and spline interpolation. The proposed method efficiently eliminating the noise and smoothness of image by integrating a de-blurring into the spline interpolation.

III. MATHEMATICAL FORMATION MODEL FOR SUPER RESOLUTION

In this section, we give a higher order restoration model for super resolution image using a sequence of low resolution images. Low resolution image means degraded, blurred and noisy version of a high resolution image and constructing a high resolution (HR) image from set of low resolution images is an inverse problem. Due to common imaging system [1] the spatial distance between the pixels is increasing causes the loss of high frequency components and image looks a degraded image with less details and pixel density.

Let us consider a down sampling factors w1 in horizontal and w2 in vertical direction and a low resolution (LR) image of size p1 x p2, denoted as L=[x1; x2:::xN], where N=p1 x p2. The high resolution (HR) image size by considering the down sampling factors is w1p1 x w2p2, denoted as Z=[y1; y2:::yK], where K=w1p1 x w2p2. By taking the high resolution image Z (s; t) and down sampling factor the low resolution image L (i; j) can be processed as

$$L(i,j) = \frac{1}{w_1 w_2} \sum_{w_1 i}^{(w_1+1)i-1} \sum_{w_2 j}^{(w_2+1)j-1} Z(s,t) \qquad (1)$$

Based on down sampling factor the low resolution image is an average of pixels of window size w1 x w2 in a high resolution image. According to the process of framework let us take g compressed, blurred low resolution images [Lm]m=1:::g of size p1 x p2 for constructing a high resolution image of size q1 x q2, where q1=w1p1, q2=w2p2. From the concept of basic imaging system [1] the low resolution image is a blurred and noise version of a high resolution image. By including the blur matrix, noise and transmission matrix the high order restoration model can be expressed as

$$L_f = H_{psf} M_f D_f Z + \eta_f ; 1 \le f \le g \qquad (2)$$

This equation can also expressed as

$$L_f = H_f Z + \eta_f \qquad (3)$$

Where H_f=$H_{psf} M_f D_f$ and H_{psf} is point spread function of optical lens of common imaging system and the size of H_{psf} is $p_1 p_2$ x $p_1 p_2$, M_f is transmission matrix of size $w_1 p_1 w_2 p_2$ x $w_1 p_1 w_2 p_2$, D_f is decimation matrix of size $(p_1 p_2)^2$x$w_1 p_1 w_2 p_2$ and η_f is noise vector of size $p_1 p_2$x1.

IV. PROPOSED METHOD FOR SUPER RESOLUTION

In this paper, we implement an algorithm for reconstruction of a high resolution image using spline interpolation and a set of low resolution images. The proposed algorithm mainly divided into three blocks. The first block is motion estimation and compensation (ME), the second one is spline interpolation and final one is de-blurring (or) sharpening filter. The adaptive full search block matching algorithm is used for motion estimation (ME) and motion compensation. Finally, HR image is reconstructed with cubic spline interpolation and de-blurring filter and the block diagram of proposed model as shown in the fig 1. According to proposed model the working procedure can be discussed as follows.

A. Full search motion estimation

Full search motion estimation algorithm [21] is used to compensate the local motion between two consecutive frames. The motion vectors of a current frame corresponding to the

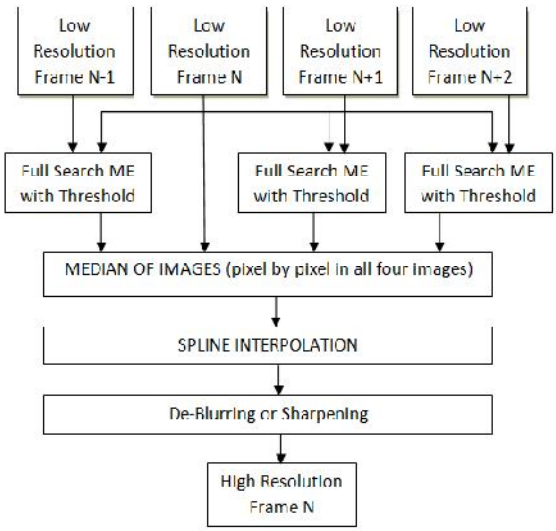

Fig. 1. Proposed SR reconstruction model

reference frame can be calculated using the MAD (Mean Absolute Difference) is shown in equation 4.

$$MAD = \frac{1}{mn}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left|r(x,y) - c(x,y)\right| \qquad (4)$$

Where r (x; y) is a reference frame and c (x; y) is a current frame. Finding a motion vectors using a full search algorithm is computational inefficient. In order to increase the performance of the algorithm and decreasing the number of computations, a full search algorithm is applied on Gray scale image and corresponding motion vectors are used on three R, G and B channels to compensate the sub-pixel motion between two consecutive frames. The number of computations further decreases by using threshold value. This threshold value can be calculated based on the estimation of the maximum motion between two consecutive frames. According to full search [21] the MAD value is compared with threshold value and if MAD value is more than the threshold value the block is moved to next consecutive block. Due to threshold value some local error are occur in compensated image and these local error can be removed by finding the median image from the four compensated images. Median image is a combination of all four frames and this image is formed by finding a median of four pixel values at same location.

B. Cubic spline interpolation and deblurring

Spline interpolation is a polynomial based interpolation in that each point on the polynomial is connected smoothly. We need a n+1 coefficients for each piece of polynomial of a degree n and first order spline is approximately equal to a linear interpolation. In a cubic interpolation the continuous and smooth spline curves [22], [23] are obtained from a series of unique polynomials between two data points. Cubic spline are used to determine the rate of change and cumulative changes over an interval. Cubic spline interpolation is used to interpolate the equally spaced and non-equally spaced data points. The mathematical spline is similar in principle. Numerical data are the points in this case. In this cubic polynomials weights are the coefficients used to interpolate the data. These coefficients are used to bend the line so that it passes through each of the data points with out any breaks in continuity.

The main aim of the cubic spline interpolaton is forming the interpolation formula at its boundaries with in the interval [24]. The interpolation is continuous in the second derivative and smooth in the first derivative. The cubic interpolation in the interval x_j and x_{j+1} using the tabulated function $R_i=R(x_i)$, i=1 ... N is given in equation 5.

$$R = ER_j + FR_{j+1} + GR_j'' + AR_{j+1}'' \qquad (5)$$

where R_j'' is second derivative of the function and

$E = \frac{x_{j+1}+x}{x_{j+1}+x_j}$, $F = 1 - E$, $G = \frac{1}{6}\left(E^3 - E\right)\left(x_{j+1} - x_j\right)^2$ and $A=\frac{1}{6}\left(F^3 - F\right)\left(x_{j+1} - x_j\right)^2$

The high resolution image constructed from a set low resolution images is shown in fig 1. Based on the method in fig 1 the motion compensated images obtained using full search motion estimation with threshold and find the median image using a three compensated fames and one original frame for decreasing the local error observed in a motion compensated images. Apply a cubic spline interpolation on median image to obtain a high resolution image. Due to spline interpolation the high resolution image losses some of the high frequency components. To recover the edges de-blurring or sharpening technique (unsharpened masking) is integrating with Spline Interpolation.

V. RESULTS AND DISCUSSIONS

In this section, we will evaluate the performance of the proposed method on different test images football, coastguard, tennis and garden using Open CV. Fig 2 shows typical video sequence frames used to evaluate the performance of our work. The whole football sequence consists of a dynamic foreground and variable background and it is best suited video frame for complex analysis. Static background and slow local motion are present in coastguard sequence. Garden sequence has a high movement on complex background. In tennis sequence the human hands are moving away from the body, it contains rigid and non-rigid objects. The proposed algorithm is compared with four other method namely Nearest neighbourhood interpolation, Bilinear interpolation, Bicubic interpolation and finally Y Chen [17] method. For the purpose of testing we generated a low resolution frames by down sampling the high resolution image by two times. The performance of this algorithms are compared using image quality assessment techniques such as subjective and objective quality measures of an image. Human eye is more sensitive to sharp change in the intensity values in an image and it is related to subjective quality of the image. To show the performance of the proposed method from other methods from subjective point of view fig 3 is included. Fig 3 shows that image in (f) reconstructed by using the proposed technique is approximately same as input high resolution image (a) as well as image reconstructed using nearest neighbourhood interpolation (b), linear interpolation (c), cubic interpolation(d) and method proposed in [17] (e). It clearly shows that proposed method gives a sharper image. The subjective quality measure is based on human dependent and it changes independtly, the objective quality measures such as Peak Signal to Noise Ratio (PSNR), Mean Average Error (MAE), Mean Square Error (MSE), Structural Similarity Index Measure (SSIM) and Signal to Noise Ratio (SNR) are used to measure the quantitative information of an image. These equations are defined in appendix by equations 6 to 11. The performance of proposed algorithm is superior compared with other interpolation and Y Chen [17] methods based on experimental results. The objective quality measures shows that proposed method outperforms all the other methods. The method proposed in Y Chen [17] and proposed method shows approximately equal results for tennis and garden sequences. Table I shows that proposed method has a higher PSNR compared to all other method and the higher PSNR will indicates a good quality image. Most of the time human visual system is to observe structural information of the viewing scene and it is highly adapted for this purpose. In order to know the perceived image distortions we need to measure structural distortions of an image. Table II compares structural similarity index measure using original frame and reconstructed frame. Higher the SSIM indicates a better image quality with less structural distortions. Table III compares the signal to noise ratio of original and reconstructed image for all test sequences. Higher the SNR indicates the better image quality. Table IV compares the mean square error between reconstructed image and original image for all test cases. Lower the MSE indicates better quality image. The comparison of root mean square (RMS) between original and reconstructed image shown in Table V and finally Table VI compares the mean average error of original image and reconstructed image. Lower value of MAE shows image has better quality.

The proposed algorithm shows a better results for video sequences by observing the PSNR comparison of different methods for football sequence is shown in fig 4. This fig 4 indicates the variation of PSNR along the number of frames for different methods. Based on fig 4 the proposed method is very effective along the video frames. However proposed method is good for restoring a human eye preserving edges.

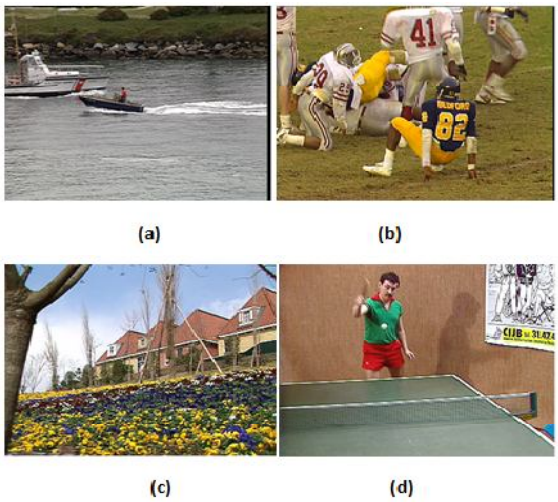

Fig. 2. Typical frames from the (a) Coastguard (b) Football (c) Garden (d) Tennis video sequence

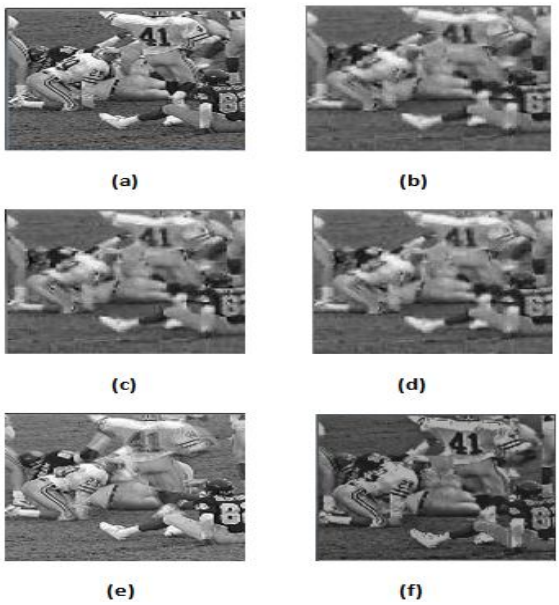

Fig. 3. The reconstructed frames of each method (a) Original image (b) Nearest neighbourhood (c) Bilinear (d) Bi-cubic (e) Y Chen [17] (f) Proposed method

TABLE I
PSNR: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS (dB)

Method	football	coastguard	tennis	garden
Nearest neighbourhood	28.24	30.03	28.46	29.97
Bilinear	29.48	30.46	29.02	30.05
Bi-cubic	30.416	31.21	30.39	29.93
Y Chen [17]	31.407	32.02	31.46	29.78
Proposed method	34.486	33.29	31.96	30.3

TABLE II
SSIM: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS

Method	football	coastguard	tennis	garden
Nearest neighbourhood	0.401	0.682	0.551	0.618
Bilinear	0.416	0.681	0.559	0.6209
Bi-cubic	0.407	0.684	0.567	0.618
Y Chen [17]	0.481	0.6234	0.574	0.717
Proposed method	0.718	0.779	0.632	0.729

TABLE III
SNR: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS(dB)

Method	football	coastguard	tennis	garden
Nearest neighbourhood	26.73	28.23	27.39	28.46
Bilinear	27.67	28.56	28.47	29.02
Bi-cubic	27.91	29.43	29.01	30.10
Y Chen [17]	28.89	29.97	29.89	30.89
Proposed method	29.97	31.42	30.43	31.23

TABLE IV
MSE: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS

Method	football	coastguard	tennis	garden
Nearest neighbourhood	93.70	62.06	89.11	62.88
Bilinear	70.39	56.1	98.6	61.77
Bi-cubic	56.78	47.3	57.12	63.52
Y Chen [17]	45.21	39.25	44.66	65.77
Proposed method	22.241	29.3	39.82	58.324

TABLE V
RMS: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS

Method	football	coastguard	tennis	garden
Nearest neighbourhood	9.68	7.878	9.439	7.93
Bilinear	8.39	7.49	9.929	7.86
Bi-cubic	7.535	6.877	7.558	7.97
Y Chen [17]	6.723	6.265	6.683	8.11
Proposed method	4.716	5.413	6.31	7.637

TABLE VI
MAE: COMPARISON OF DIFFERENT SUPER RESOLUTION METHODS

Method	football	coastguard	tennis	garden
Nearest neighbourhood	30.9	21.33	36.62	41.89
Bilinear	30.151	21.67	37.03	40.54
Bi-cubic	30.45	20.66	37.67	41.89
Y Chen [17]	26.6	23.4	39.12	42.36
Proposed method	20.7	20.67	38.76	42.9

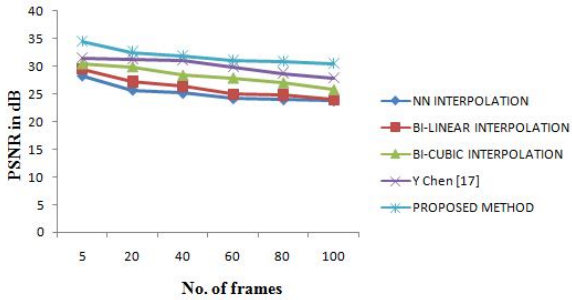

Fig. 4. The PSNR (dB) comparison of different high resolution reconstructed methods using football video sequence.

CONCLUSION

Super resolution reconstruction techniques are used in many different applications for the requirement of quality. Super resolution reconstruction is an emerging technology used in Military, Satellite and Cellular networks for constructing a high resolution image from a set compressed low resolution images. In this work, we proposed a spline interpolation based super resolution algorithm using multiple low resolution frames. Experimental results shows that proposed algorithm is good for preserving a high frequency components such as edges. The proposed algorithm has been tested on different test sequences using image quality assessment technique such as PSNR, SSIM, SNR, MSE, RMS and MAE. Based on experimental results the performance of the proposed algorithm is visually better compared to other methods.

APPENDIX

The structural similarity index measure (SSIM) between an original image x (i; j) and test image y (i; j) is given by

$$Q = \frac{4\sigma_{xy}\bar{x}\bar{y}}{\left(\sigma_x^2 + \sigma_y^2\right)\left(\bar{x}^2 + \bar{y}^2\right)} \tag{6}$$

Here $\bar{x}, \bar{y}$ are the mean of original and reconstructed images and σ_{xy} is the co-variance between original and reconstructed images and σ_x^2, σ_y^2 are the variance of original and reconstructed images The high value of SSIM indicates a good quality image.

The mean square error (MSE) between an original image $r(i,j)$ and test image $t(i,j)$ is given by

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left((r(x,y)) - (t(x,y))^2\right) \tag{7}$$

Where MN is total number of pixels in an image and less value of MSE indicates a good quality image

The PSNR (Peak Signal to Noise Ratio) is given by

$$PSNR = 10log\left(\frac{[max(r(x,y))]^2}{MSE}\right) \tag{8}$$

The lower value of PSNR indicates poor quality of the image

The signal to noise ratio between an original image $r(i,j)$ and test image $t(i,j)$ is given by

$$SNR = 10Log_{10}\left[\frac{\sum_{x=0}^{p-1}\sum_{y=0}^{q-1}[r(x,y)]^2}{\sum_{x=0}^{p-1}\sum_{y=0}^{q-1}[r(x,y)-t(x,y)]^2}\right] \tag{9}$$

The higher value of SNR indicates good quality of the image

The MAE (mean average error) between an original image $r(i,j)$ and test image $t(i,j)$ is given by

$$MAE = \frac{1}{pq}\sum_{x=0}^{p-1}\sum_{y=0}^{q-1}|r(x,y) - t(x,y)| \tag{10}$$

Where pq is total number of pixels in an original image. Lower the value of MSE indicates image is good quality The root mean square value (RMS) is

difference between an original image r (i; j) and test image t (i; j) is given by

$$RMS = \sqrt{MSE} \tag{11}$$

The lower value of RMS indicates a good quality image.

REFERENCES

[1] N. Maheta, "A comparative study of image super resolution approaches," in Electronics Computer Technology (ICECT), 2011 3rd International Conference on, vol. 1. IEEE, 2011, pp. 129–133.

[2] S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: a technical overview," Signal Processing Magazine, IEEE, vol. 20, no. 3, pp. 21–36, 2003.

[3] P. Vandewalle, S. S¨u, M. Vetterli et al., "A frequency domain approach to registration of aliased images with application to super-resolution," EURASIP Journal on Advances in Signal Processing, vol. 2006, 2006.

[4] Z. Xiong, X. Sun, and F. Wu, "Robust web image/video superresolution," Image Processing, IEEE Transactions on, vol. 19, no. 8, pp. 2017–2028, 2010.

[5] K.-W. Hung and W.-C. Siu, "Single image super-resolution using iterative wiener filter," in Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on. IEEE, 2012, pp. 1269–1272.

[6] N. Bharati, A. Khosla, and N. Sood, "Image reconstruction using cubic b-spline interpolation," in India Conference (INDICON), 2011 Annual IEEE. IEEE, 2011, pp. 1–5.

[7] S. Kumar Maurya, P. Kumar Mishra, R. Kumar Singh, and A. Kumar Misra, "Image enhancement by spline interpolation and adaptive power spectrum cut-off of filtered images," in Advances in Engineering, Science and Management (ICAESM), 2012 International Conference on. IEEE, 2012, pp. 423–428.

[8] C. Kumar, V. Ananthashayana et al., "Super resolution reconstruction of compressed low resolution images using wavelet lifting schemes," in Computer and Electrical Engineering, 2009. ICCEE'09. Second International Conference on, vol. 2. IEEE, 2009, pp. 629–633.

[9] R. Tsai and T. S. Huang, "Multiframe image restoration and registration," Advances in computer vision and Image Processing, vol. 1, no. 2, pp. 317–339, 1984.

[10] J. Clark, M. Palmer, and P. Lawrence, "A transformation method for the reconstruction of functions from nonuniformly spaced samples," Acoustics, Speech and Signal Processing, IEEE Transactions on, vol. 33, no. 5, pp. 1151–1165, 1985.

[11] Y.-M. Zhu, "Generalized sampling theorem," Circuits and Systems II: Analog and Digital Signal Processing, IEEE Transactions on, vol. 39, no. 8, pp. 587–588, 1992.

[12] A. M. Tekalp, M. K. Ozkan, and M. I. Sezan, "High-resolution image reconstruction from lower-resolution image sequences and space-varying image restoration," in Acoustics, Speech, and Signal Processing, 1992. ICASSP-92., 1992 IEEE International Conference on, vol. 3. IEEE, 1992, pp. 169–172.

[13] M. Irani and S. Peleg, "Improving resolution by image registration," CVGIP: Graphical models and image processing, vol. 53, no. 3, pp. 231–239, 1991.

[14] A. J. Storkey, "Dynamic structure super-resolution," Advances in Neural Information Processing Systems, pp. 1319–1326, 2003.

[15] V. Fedak, Z. Veres, and A. Nakonechny, "Image and video superresolution via accurate motion estimation," in Perspective Technologies and Methods in MEMS Design (MEMSTECH), 2010 Proceedings of VIth International Conference on. IEEE, 2010, pp. 223–225.

[16] X. Zhang, R. Xiong, S. Ma, and W. Gao, "A robust video superresolution algorithm," in Picture Coding Symposium (PCS), 2010. IEEE, 2010, pp. 574–577.

[17] Y. Chen, W. Jin, L. Wang, C. Liu, and W. Chen, "Robust multiframe super-resolution reconstruction based on regularization," in Computer Symposium (ICS), 2010 International. IEEE, 2010, pp. 408–413.

[18] D. J. Mudugamuwa, X. He, and W. Jia, "Efficient super-resolution by finer sub-pixel motion prediction and bilateral filtering," in Multimedia and Expo (ICME), 2012 IEEE International Conference on. IEEE, 2012, pp. 800–805.

[19] Y. Anagun and E. Seke, "Super resolution using variable size block matching motion estimation with rotation," in Innovations in Intelligent Systems and Applications (INISTA), 2012 International Symposium on. IEEE, 2012, pp. 1–5.

[20] T. Zhang and X. Yu, "A contourlet-based image super-resolution approach," in Audio, Language and Image Processing (ICALIP), 2012 International Conference on. IEEE, 2012, pp. 375–378.

[21] S. I. A. Pandian, G. J. Bala, and B. A. George, "A study on block matching algorithms for motion estimation," International Journal, vol. 3, 2011.

[22] H. Hou and H. Andrews, "Cubic splines for image interpolation and digital filtering," Acoustics, Speech and Signal Processing, IEEE Transactions on, vol. 26, no. 6, pp. 508–517, 1978.

[23] J. MIHALI´K, J. ZAVACKY´, and I. Kuba, "Spline interpolation of image," Radioengineering, vol. 4, no. 1, pp. 221–230, 1995.

[24] W. H. Press, S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery, Numerical recipes 3rd edition: The art of scientific computing. Cambridge university press, 2007.

★★★