iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5 **Issue:** X **Month of publication:** October 2017

DOI: http://doi.org/10.22214/ijraset.2017.10235

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue X, October 2017- Available at www.ijraset.com

Image/Video Reconstruction Using a Novel Hybrid Method

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Abstract: Image/Video super-resolution is an essential part for various technologies, including Video Surveillance, Robotics, Medical applications and Multimedia. Aiming at improve the super resolution of an image/video reconstruction a novel hybrid method combining both super resolution and particle swarm optimization algorithm is proposed. In the process of image/video reconstruction, initially to up-sample the frames a non uniform interpolation method is applied but the frames are still blurry. So to estimate the blur a adaptive regularization approach is used, it consists of fidelity and regularization terms and they are updated by adaptive iteration process .To preserve the edges and remove the noise a Relaxed median filter is used it performs well at any type of noise. Then the reconstructed frames are optimised using the particle swarm optimization algorithm which includes particle input, particle position, motion equations and fitness function .Image/Video reconstruction using existing methods is poor due to fixed iteration step size. To overcome that limitation, in proposed method the iteration step size is adaptively selected based on the fitness value, when it is reached minimum the estimated super resolution image/video is optimised. The quality factors like PSNR, NAE, IEF, Correlation Coefficient and Structural Content are very much improved than existing methods.
Keywords: Image/Video reconstruction, Non uniform interpolation, Blur estimation, Adaptive Regularization, PSO, Relaxed median filter.

I. INTRODUCTION

Image/Video super resolution plays a key role in surveillance systems,medical field, image and video data transmission and multimedia. The acquired image may get affected by the Gaussian noise during transmission, Impulse (Salt and Pepper) noise from switching circuits and blur due to the shake of camera or motion of object. Generally, Impulse and Gaussian noises produce grain and pimple like effects on images. So to remove such type of artefacts earlier traditional interpolation methods like bilinear, bi-cubic and nearest neighbourhood are used but these are used to compare the missing intermediate pixels in the enlarged high resolution (HR) grid by averaging the original pixel of low resolution (LR) with fixed filters. Super Resolution algorithms aim at estimating the missing high resolution detail that is not present in the original image by adding new possible high frequencies. For this we have two methods one is multi frame super resolution and another one is single image super resolution Multi image super resolution is the process of estimating high resolution (HR)[4] image by fusing the low resolution (LR) images. Video super resolution is the process of estimating the high resolution video by fusing one or multiple low resolution videos is used to increase spatial or temporal resolution [2].

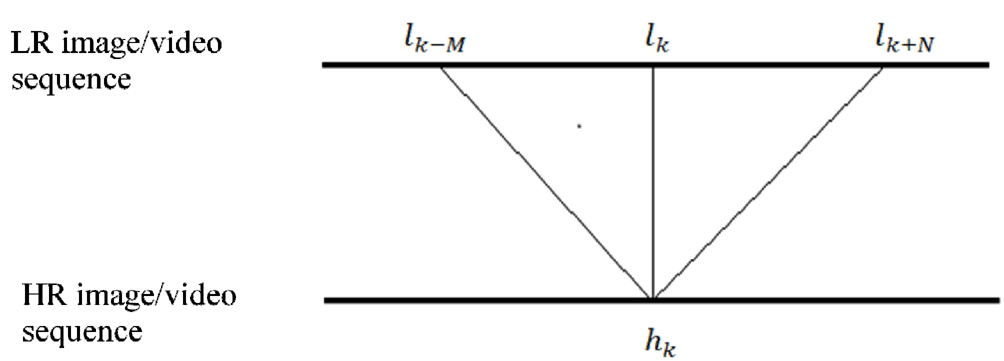

Fig.1 A sliding window of size M+N+1 is defined around each LR frame l_i.And the each HR frame $h_i$reconstructed by fusing the LR frames inside window

Multi frame super resolution can be classified as Interpolation based approach, Frequency domain approach and regularization based approach. In non uniform interpolation method (NUI) approach entire reconstruction process is not guaranteed because

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registration errors are not taken in to the account. In Frequency domain based approach (FFT) high frequencies are spread across the multiple LR images in form of aliased spectral frequencies, but the assumption is that the HR image is band limited. Super resolution algorithms basically having ill posed problems due to in sufficient number of LR images or ill conditional blur operations. So to convert the ill posed problem into good problem a regularization approach is used. These methods adopt a Bayesian approach [9], according to which the information that can be extracted from LR images about the unknown signal HR image is contained in the probability function of the unknown. The usual methods of regularisation are HMRF, Tikhonov and Total Variation(TV)[10] and the main problem is selection of regularization coefficient .In the above methods the regularization coefficient is constant so the reconstruction result is ideal and the iterative size is still certain real number this leads to poor reconstruction to overcome that in proposed method(a new hybrid method combined both SR and PSO algorithm) the iteration step size is depend on the fitness value[6], when it is reached minimum the estimated super resolution image/video is optimised.PSO[8] as an efficient optimization method is easy to implement, Has strong global convergence ability, robustness and suitable for solving optimization functions in complex environment.

II. LITERATURE SURVEY

The LR degradation model and blur estimation taken from paper E. Faramarzi, D. Rajan, and M. P. Christensen, "Blind Super resolution for the real life video sequences [3]",in this a fixed iteration process is used. So the adaptive iteration process taken from the Wu Chunli, Liu Cuili, Li Xiaowan,"Anew adaptive iterative regularized algorithm for super resolution image reconstruction''[6]. PSO algorithm is taken from the paper Wenjing Yu and Mingjun Zhang, "A mixed particle swarm optimization algorithm's application in image/video super resolution reconstruction" [8],it is used to optimize the reconstructed image.

III. RELATED WORK

Proposed method is organised as fallows A. Proposed model B. Degradation model C.Super resolution (SR) method D. Super resolution image/video estimated using PSO.

A. Proposed Model

The propose model is a novel hybrid method it includes three parts they are observe the low resolution (LR) images from the degradation model which is explained in below section. The next part is the prcess of getting high resolution (HR) image from observed low resolution (LR) images it is a ill posed problem and it is effectively achieved by selecting adaptive regularization approach .The estimated image is then optimized to as super resolution image using last section of the hybrid model that is PSO .The HR frames, particle velocity and particle position updated iteratively using the fitness function.

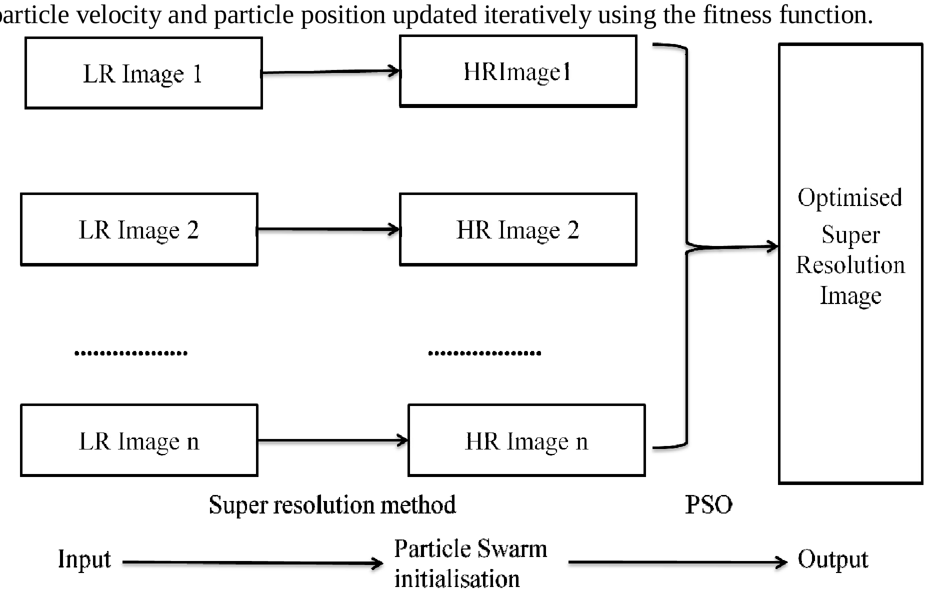

Fig. 2 A new hybrid method for image/video reconstruction

B. Degradation Model

In this model a High resolution (HR) image/video (further it will be reconstructed) is set as input of the model and the observed low resolution images will get at the output end of the model.

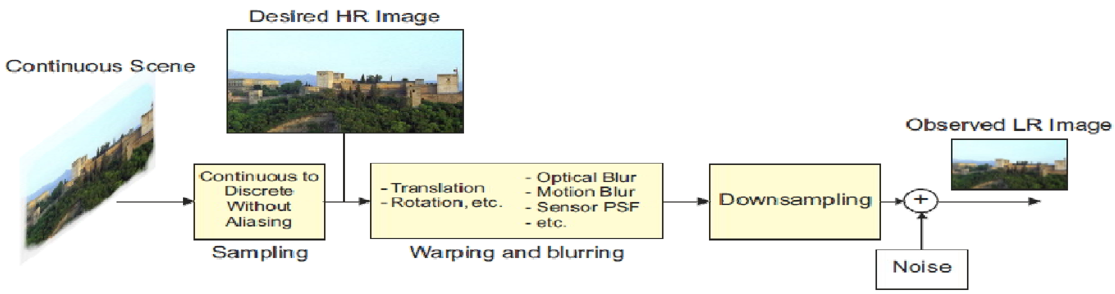

Fig. 3A degradation model to create low resolution images from high resolution image

It is shown in Fig. 3, image/video transferring from high resolution to low resolution it will affect by the motion blur, atmospheric blur, down sampled with factor and added some random noise. The degradation (observed) model is illustrated mathematically by the equation (1).

$$l_i = DM_iB_ih + g_i \tag{1}$$

where$l_i$is the observed low resolution image sequence from high resolution image, M_i is the geometric deformation matrix including translation and rotation of the i^{th} low resolution image, $B_i$is the blur kernel or point spread function (PSF), D is the reduced sampling matrix and g_i is additive random noise.

C. Blur estimation using Super Resolution (SR) method

1) *Frame up-sampling:The observed low resolution images are up-sampled using non uniform interpolation method (NUI) and it provides output as averaging four adjacent pixels.*

$$l_i = DM_iB_ih + g_i \tag{2}$$

where D is the up-sampling matrix and g_i is the random noise. To express more clearly and conveniently the equation to simplified as

$$l_i = W_ih + g_i \tag{3}$$

Among the equation (3) $W_i$is the product of D, M_i, and B_i. To remove the noise relaxed median filter is applied, it preserved the edges and improved structural content of the frame. Even though the frames are up-sampled but they are still blurry. So to estimate the blur and high resolution frames adaptive regularization approach is applied.

2) *Frame de-blurring using adaptive regularization approach*

$$f = argmin(\sum_{i=1}^{p} \rho(\, l_i - W_ih) + \lambda(i)\beta(h)\,) \tag{4}$$

Among them,$l_i - W_ih$ is the i[th] low resolution image.$\rho(.)$ is fidelity term of the reconstructed image which gives error between the observe image and reconstructed image. $\beta(.)$ is the regularization term which ensures the smoothness of the reconstructed image. λ(i) is the regularization parameter ,which maintains balance between the fidelity term and regularization term. $\rho(l_i - W_ih)$ is expressed as

$$\rho(l_i - W_ih) = ||l_i - W_ih||^2 \tag{5}$$

$$\beta(h) = ||\Delta h||^2 \tag{6}$$

whereΔ is the stability high pass filter or laplacian operator which improves smoothness and here L2 norm is used to increase robustness of the algorithm to noise.

3) *Adaptive iterative coefficient*

The adaptive iteration coefficient is used to maintain balance between both fidelity term and regularization coefficient.

$$\lambda(i) = \phi\left(T_i(h).\frac{\beta(h)}{\rho(l_i - W_i h)}\right) \quad (7)$$

$$\lambda(i) = ln\left(T_i(h).\frac{\beta(h)}{\rho(l_i - W_i h) + \eta} + 1\right) \quad (8)$$

$$T_i(h) = \frac{\sum_{i=1}^{p} \rho(l_i - W_i h)}{\rho(l_i - W_i h)} \quad (9)$$

In order better reconstruction $\lambda(i)$ should be greater than 1and inversely proportional to the $\rho(.)$. In the equation (7),$\phi(.)$ is chosen as logarithmic growth function to robustness of the algorithm . Equation (9) is a scaling function and η is a small positive real number.

4) High resolution frame estimation

The hybrid method is used to solve the minimum value of the equation (4) the basic idea of this algorithm is fast converge along the negative gradient direction to find the minimum. So to achieve minimum value the equation (10) is iterated adaptively up to satisfy condition of equation (16).Once the fitness function is satisfied is the estimated super resolution image/video is optimized.

$$f' = f - \sigma\{\sum_{i=1}^{p} M_i^T B_i^T D_i^T \theta(l_i - DM_i Bf) + \lambda(i)\Upsilon(f)\} \quad (10)$$

where θ(.),Y(.)are the fidelity and regularization terms and M_i^T, B_i^T *and* D_i^T are the series of reconstruction of motion estimation,de-blurring operation an up-sampling operationand the iterative step size is given as

$$\sigma = \frac{2}{p}\left(\frac{k_1 k_2}{k_1 k_2 \Phi_{max}[\Delta^T \Delta]\lambda(i) + 1}\right) \quad (11)$$

where k1,k2 are down sampling factors and p is number of low resolution images.

D. Optimizing the high resolution image using PSO

The PSO basic formula is given in the equation (12) and (13), among them the factors c1,c2 are the non negative constants,r1,r2 are the random numbers, $v_i$is the particle velocity, x_i is the particle position, w is the memory behaviour of the particle,$p_{ib}$is the best location for single particle and p_{gb} is the best location for entire swarm.

$$v_{ib}^{t+1} = wv_{ib}^t + c_1 r_1(p_{ib} - x_{ib}^t) + c_2 r_2(p_{gb} - x_{ib}^t) \quad (12)$$

$$x_{ib}^{t+1} = x_{ib}^t + v_{ib}^{t+1} \quad (13)$$

From equation (12), when the particle swarm approaches the optimal location $p_{gb}$the speed is updated by wv_{ib}^t.
If w<1, the speed is getting smaller and when it is optimal the convergence speed is fast.

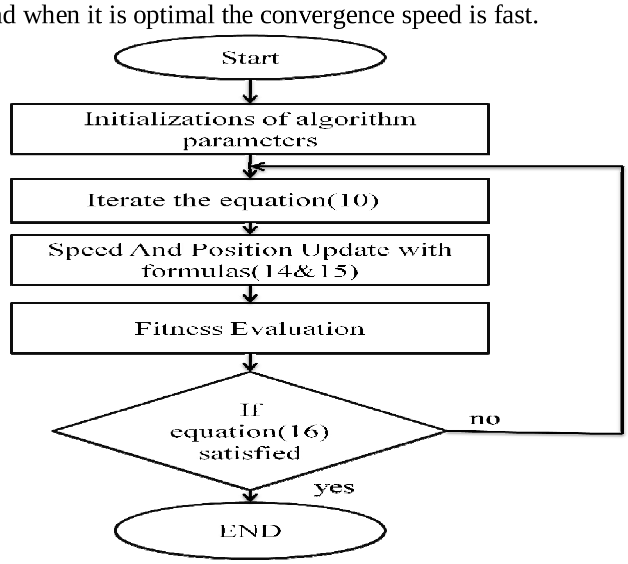

Fig.4. Flow chart of proposed method

1) *Speed and position updating process*

The speed and position of the particle updated using equations (14) and (15),if the new is greater than the maximum value the maximum value is set similarly the new value is less than maximum value,the minimum value is set.

$$v_{ib}^{t+1} = r_2 w v_{ib}^{t} + c_1(1-r_2)r_1(p_{ib} - x_{ib}^{t}) + c_2(1-r_2)(1-r_2)(p_{gb} - x_{ib}^{t}) \quad (14)$$

$$x_{ib}^{t+1} = x_{ib}^{t} + v_{ib}^{t+1} \quad (15)$$

2) *Fitness function evolution for image/video super resolution*

This fitness function is used to perform the number of iterations of above all equations .If the fitness value reaches the minimum the estimated super resolution frame is optimized and iterations should be stopped.

$$ff = \min\left(\sum_{i=0}^{255}\left(\frac{m_i}{m} - \frac{ni}{n}\right)\right) \quad (16)$$

wherem_i, $n_i$are the number of pixels of gray level low resolution image and high resolution image, m, n are the respectively the number of pixels of the low resolution image and high resolution image.

3) *Steps to optimize the super image/video resolution*

a) From the degradation model the sequential i frame image sequence in the image/video is selected as the low resolution image vector

$$L_1 = [l_{11}, l_{12}, l_{13}, \ldots\ldots l_{1m},\ L_2 = [l_{21}, l_{22}, l_{23}, \ldots\ldots l_{2m},\ \ L_i = [l_{i1}, l_{i2}, l_{i3}, \ldots\ldots l_{im}$$

b) Initial particle swarm size and individual value, let a number of initial particle swarm size as L_i and after estimated through super resolution algorithm get the high resolution images as H_i

$$f'_1 = [f'_{11}, f'_{12}, f'_{13}, \ldots\ldots f'_{1m}, f'_2 = [f'_{21}, f'_{22}, f'_{23}, \ldots\ldots f'_{2m}, f'_i = [f'_{i1}, f'_{i2}, f'_{i3}, \ldots\ldots f'_{im}$$

c) Initialize algorithm parameters, calculate the fitness value based on the fitness function and the most efficient fitness value is selected as global optimal solution $p_{gb}$and p_{ib} is selected as the individual optimal solution of first frame high resolution image sequence vector.

d) Update the particle position and particle velocity using the given formulas in equations (14) and (15).

e) Fitness evaluation function check the termination condition, if the termination condition satisfied iteration is stopped, if not go to the step 4.

IV. EXPERIMENTAL RESULTS

Here the experimental results showed both in visual effects evaluation and objective quantitative evaluation. For the quantitative evaluation some quality factors are chosen below.

A. *Quality measuring factors*

1) Peak signal to noise ratio

$$PSNR = 10log_{10}\left(\frac{255^2}{h(i,j) - f'(i,j)}\right) \quad (17)$$

Where *h(i,j)* is the original image, *f(i,j)*is the estimated image

2) Normalized absolute error

$$NAE = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\frac{(h(i,j) - f'(i,j))}{h(i,j)} \quad (18)$$

Where *h(i,j)* is original image and *f(i,j)* is estimated image

3) Image enhancement factor

$$IEF = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\frac{(l(i,j) - h(i,j))}{(f'(i,j) - h(i,j))} \quad (19)$$

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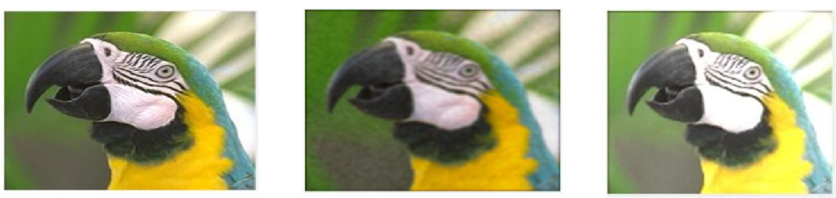
Where *l(i,j)* is the noisy image.

4) Structural content and cross correlation coefficient.
These are calculated using MATLAB functions.

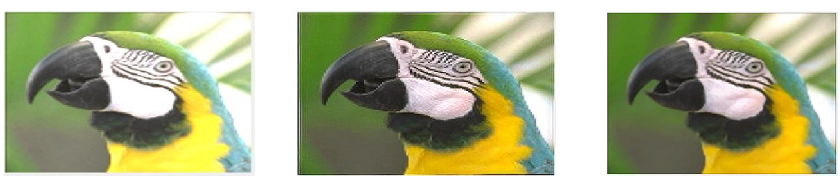
B. Simulation experimental results of image & video

The high resolution parrot image as shown Fig. 5(a) is taken as the reference which is of 256x256 pixel size and in RGB colour format. To get the low resolution image as shown in the Fig. 5(b), RGB colour model image is converted in to Ycbcr for better quality assessment and the down sampling factor of horizontal and vertical is 2, the blur kernel 3x3size window has taken as point spread function(PSF) ,it is applied geometric transformation both translation and rotation and convolved with original reference image then it is added some random Gaussian noise(mean equal to zero and variance is taken as 0.0003).

Reconstruction of the original parrot image using different resolution methods has shown in the Fig. 5. Where Fig.5(c) shows the image reconstruction using bi-cubic interpolation method, obviously the reconstructed image poor in resolution it is a traditional image enhancing method having PSNR is 14.782db, Fig. 5(d) shows the image reconstruction using blind de-convolution method using MATLAB default function which performed better than bi-cubic method having PSNR is 18.203db. but still not up to the desired level, Fig. 5(e) shows the image reconstruction super resolution method using fixed size of iteration step ,it improved the quality of image resolution compare to both previous methods but using certain real number as iteration step size the reconstructed image not up to the desired level and having PSNR is 22.926db and Fig.5(f) shows the image reconstruction using proposed method ,the iteration step is selected adaptively and relaxed median filter is used to remove the Gaussian noise .The reconstructed image has better image quality compare to above methods and the PSNR value is 27.650 db ,the fitness value and qualitative analysis among all the reconstruction methods are also given has shown in the Table I.



(a) (b) (c)



(d) (e) (f)

Fig.5Comparison resolution of parrot image using different image reconstruction methods (a)-Original image (b)-LR image (c)-Bi-cubic Interpolation
(d)-Blind de-convolution(e)-SR method (f)-Proposed method.

TABLE I
Comparison Of Various Quality Factors Of Image Among Existing Methods And Proposed Method

Quality Factor	Bi-cubic method	Blind de-convolution	Super Resolution	Proposed (fitness value=0.036)
PSNR	14.782	18.203	22.926	27.650
IEF	0.974	0.987	6.351	18.838
CC	0.960	0.969	0.935	0.976
NAE	0.329	0.234	0.054	0.038
SSIM	0.547	0.549	0.575	0.581

The high resolution Bus video as shown Fig. 6(a) is taken as the reference which is of 352x288pixel size, frame rate is 25 fps, bits per pixel are 24 and in RGB24 colour format. To get the low resolution video frames as shown in the Fig. 6(b), RGB colour model frame is converted in to Ycbcr for better quality assessment and the down sampling factor of horizontal and vertical is 2,the blur kernel 3x3size window has taken as point spread function(PSF) ,it is applied geometric transformation both translation and rotation and convolved with original reference image then it is added some random Gaussian noise(mean equal to zero and variance is taken as 0.08).

Reconstruct of the original parrot video using different resolution methods has shown in the Fig. 6. Where Fig.6(c) shows the video reconstruction using bicubic interpolation method, it is a traditional video enhancing method having poor resolution and PSNR is 17.216db, Fig. 6(d). shows the video reconstruction using blind deconvolution method using MATLAB default function which performed better than bi-cubic method having PSNR is 17.259db., Fig. 6(e) shows the video reconstruction super resolution method using fixed size of iteration step ,it improved the resolution compare to both previous methods but using certain real number as iteration step size hence reconstruction is not up to the desired level and having PSNR is 21.662db and Fig.6(f) shows the video reconstruction using proposed method, the iteration step is selected adaptively and relaxed median filter is used to remove the Gaussian noise .The reconstructed image has better image quality compare to above methods and the PSNR value is 23.246db ,the fitness value and qualitative analysis among all the reconstruction methods are also given has shown in the Table II.

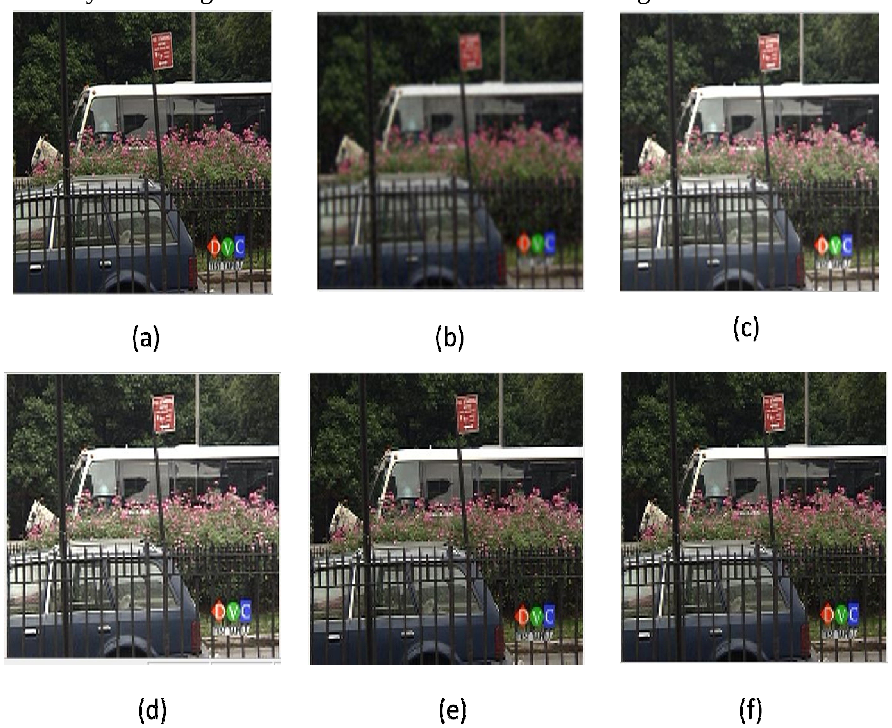


Fig.6Comparison of resolution of Bus video using different video reconstruction methods (a)-Original image (b)-LR image (c)-Bicubic Interpolation (d) -Blind deconvolution (e)-SR method (f)-Proposed method.

Table ii

Comparing various quality of video sequence among existing methods and proposed method

Quality Factor	Bicubic method	Blind deconvolution	Super Resolution	Proposed (fitness value=0.133)
PSNR	17.216	17.259	21.662	23.246
IEF	0.844	0.853	2.351	3.842
CC	0.885	0.920	0.897	0.936
NAE	0.371	0.346	0.143	0.133
SSIM	0.524	0.622	0.626	0.794

V. CONCLUSION

Image/video reconstruction is a challenging problem due to complex nature of the motion fields.In this paper to improve the super resolution of an image/video reconstruction a novel hybrid method is proposed and it is effectively estimated the blur using fidelity term with adaptively iterating process. Fidelity and regularization parameter areupdated using adaptive iteration step size. The fixed iteration process is used in existing methods, so it leads to poor reconstruction .To overcome that, in proposed method the iteration step size is selected on the basis of fitness value, when it is reached minimum the estimated super resolution image/video is optimised and calculated the fitness value using the fitness function. The improvement in resolution is observed both visually and using qualitative analysis like PSNR, IEF.etc. Further this paper can improve using some new optimization algorithms like TLBO,JAYA.etc.

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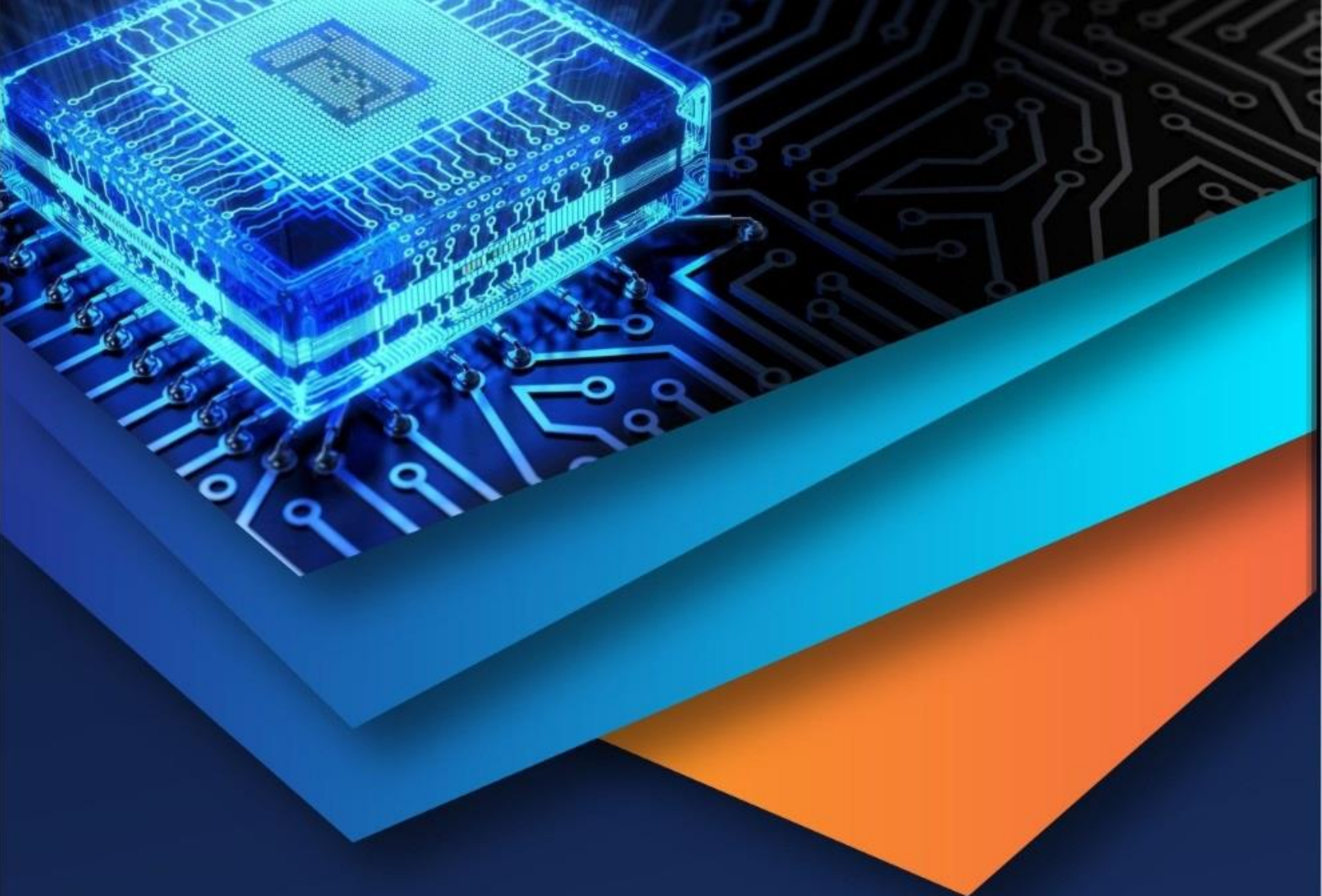

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