Development of Robust Video Super Resolution Restoration Using Recursive Integration and Radial Sharpening

Satyendra Pratap Singh[1], Prof. Harsh Mathur[2]

[1]*Mtech. Scholar,* [2]*Research Guide*

Department of Computer Science and Engineering, IES, Bhopal

Abstract - A low resolution video sequence having the problem of enhancing each frame by splitting information of many adjacent frames is an interesting and well-challenging work. The fundamental objective of super resolution scheme is to reconstruct a high resolution and high quality video sequence from a low quality low resolution video sequence. Super resolution is one of the digital image processing problems now days due to huge usage and availability digital cameras and camcorders. To overcome low resolution issue in real life video sequences an efficient video sequence restoration scheme based on recursive integration followed by radial sharpening has been proposed in this work. Implementation and simulation of proposed work has been done on Matlab and simulation of proposed work has done on Matlab Simulink simulation environment. The results comparison of proposed work with existing work shows the efficiency of proposed work with respect to existing work.

Keywords - Video Reconstruction, Recursive Integration, Radial Sharpening, Gaussian Noise, Motion Blur.

I. INTRODUCTION

A video camera is required to deliver a video sequence at desired frame-rate and spatial resolution. Fulfilling this demand is a challenge for some applications due to physical limitations of imaging systems. Obviously, high-resolution, high frame-rate video of a scene is desirable because it contains more recognizable details, and is more pleasant. A trade off exists between frame-rate and resolution, where improving both at the same time is either not possible or leads to an expensive or heavy imaging device, which is not practical for many applications. As an instance, consider a consumer video recorder that uses CMOS image sensors. To increase resolution, one approach is to increase pixel density of the image sensor. This may decreases the Signal to Noise Ratio (SNR) of the sensor output, when the size of the sensor remains the same and thus the area of each pixel on the chip decreases.

The problem of enhancing each frame of a low-resolution video sequence by exploit- ing information of many adjacent frames is an interesting and well-researched subject in the area of signal processing, which is called “multi-frame super-resolution”. In applications such as medical imaging or remote sensing, a high frame-rate sequence of the object may not be generally a must. While desirable high-resolution images are not achievable using the available device, a sequence of frames may be used for gen- erating one high-resolution image. In fact, multi-frame super-resolution algorithms were proposed basically for producing one single high-resolution image of the scene by taking more than one frame and then combining their information. Therefore, super-resolution techniques can be applied to a wide variety of applications and are not limited to the video enhancement.

Image resolution is determined by two main factors. Blurring, due to optical limits and various other processes (like the effect of the atmosphere and motion blur, for example), results in soft images, while low-sensor density of the imaging device causes aliasing. Signal processing based super-resolution (SR) methods are typically concerned with overcoming the resolution limitation resulting in aliasing (although such techniques do take blur into consideration). In this context, ‘resolution’ refers to the sampling interval, or pixel size. Coarse sampling (pixels of relatively large size) results in ‘low resolution’ images, while ‘high resolution’ images correspond to fine sampling (pixels of relatively small size) . This is in contrast to optical super-resolution where the aim is to beat the diffraction limit [40]. Optical SR methods are expensive and are usually developed to enhance the resolution of an already expensive imaging system [41] that is capable of producing very high resolution images (up to the diffraction limit). Henceforth, the term ‘super-resolution’ shall be used exclusively to refer to the process of overcoming the sensor density limitation using signal processing methods.

Super-resolution, also spelled as super resolution and superresolution, is a term for a set of methods whose aim is to increase the spatial resolution of videos or images.

Terms such as "upscale" and "upsize" also describe an increase of resolution in either image processing or video editing. Typical domains of application of super-resolution include medical imaging [1], remote sensing [2, 3], target detection and recognition [3, 4], radar imaging [5], forensic science [6], and surveillance systems [7].

The principles behind multi-frame and single-image SR methods are deeply different. The former uses information from several different images to create one single upsized image. Algorithms try to extract and combine "real" details from every available frame. Single-image SR, instead, refers to more sophisticated methods (the problem is more difficult and necessarily ill-posed), which, starting from as little as one single input image, attempt at artificially synthesizing new details.

There are several image processing application requires high resolution images for processing and analysis. The desire for high resolution images came from two principal application areas: improvement of pictorial information for human interpretation; and helping representation for automatic machine perception. Image resolution describes the amount of information contained by images. Lower resolution less would be the amount of information, higher resolution more would be amount of information in images. Resolution of a digital image can be classified in many ways: pixel resolution, spatial resolution, spectral resolution, temporal resolution, and radiometric resolution.

Spatial resolution: A digital image is made from small picture elements called pixels. Spatial resolution refers to the pixel density in an image and measures in pixels per unit area.

The spatial resolution of an image is limited by the image sensors or the image acquisition devices. The modern image acquisition devices are using charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) as active pixel sensor.

II. SYSTEM MODEL

Super resolution is an image reconstruction problem which generates a high resolution image from a number of low resolution images, each differs in sub-pixel shift parameter, blur parameter etc. from one another. Each low resolution image that has new unique information for the high resolution image is useful for the super resolution technique.

It is a method of extrapolation i.e. the process of estimation, beyond the original observation interval. As figure 2.1 explains this; let a scene is being captured by a camera of (3X3) resolution. A unit of sensor as known as pixel has a fixed dimension. The circle inside each pixel shows the approximate photosensitive area of the pixel hence the light falling on the pixel other than the photosensitive area cannot be captured by LR frame1. Therefore the use of extrapolation enables taking information from another observation i.e. LR frame2 with sub-pixel shift of LR image 1. An important point to be considered is that only images with sub-pixel shift only can provide non-redundant information (motion vectors), to visualize it the second column of pixel for LR image 2 are drawn transparent showing the un-overlapped photo sensitive area.

It uses extrapolation for resolution enhancement in the reconstructed image. The high frequency components for HR images are extrapolated from multiple numbers of LR images. It applies 2D-signal processing techniques to eliminate hardware limitations.

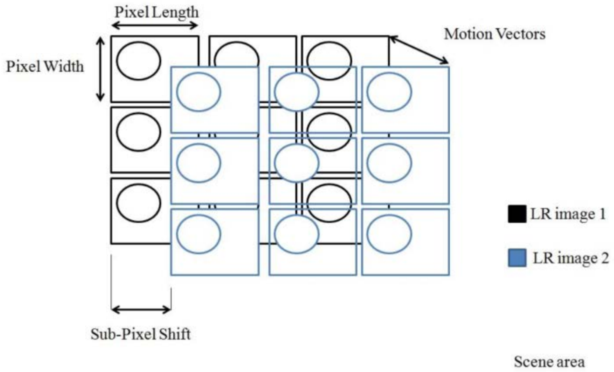

Figure 2.1 Two low resolution images with sub- pixels shift and non redundant visual information.

The set of low resolution images are first mutually aligned on a common high resolution lattice. This is generally referred to as image registration. The aligned pixel values (usually resulting in a non-uniform sampling) are then interpolated over the reference high resolution lattice to obtain a fused high resolution image as shown in figure 2.2.

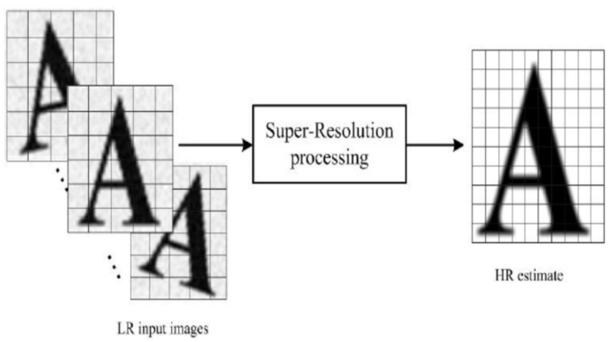

Figure 2.2 Relationship between low resolution images and high resolution image.

A subsequent de-blurring of the fused image results in a higher resolution image provided that a sufficient number of low resolution images are available and that the image alignment is carried out to sub-pixel accuracy. While these subtasks have been separately identified for conceptual clarity, they are often performed in a joint fashion.

III. PROPOSED WORK

A digital video sequence is in fact the result of 3-dimensional time-space sampling of the scene. Each frame is a 2D representation of the scene, spatially sampled at a time instance. Multiple frames along time axis add the third dimension to the sequence, representing temporal sampling of the scene. Image sensor plays the important role of spatial sampling of the scene.

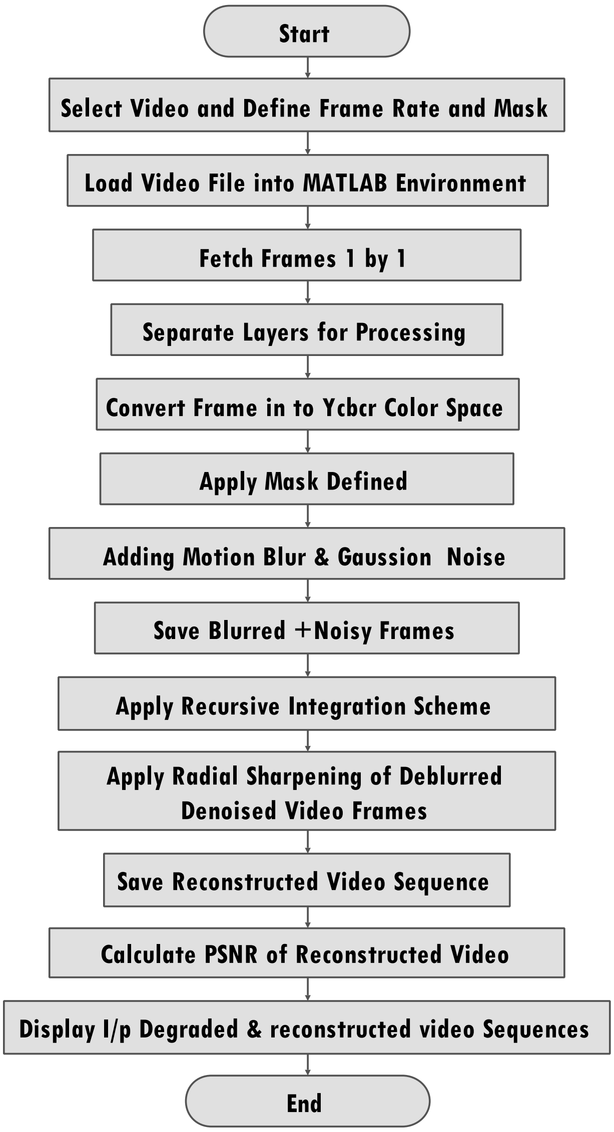

Figure 3.1 Flow chart of proposed work.

The signal recorded by each light sensor unit is directly related to the number of photons detected on its surface. This number is related to the average light intensity in the corresponding area, the exposure time, and the area of each light sensor. The number of photons received from each point of the scene determines the accuracy of its intensity estimation in presence of different sources of noise. To enhance the frame resolution recursive integration and radial sharpening approach has been proposed in this work. The process flow of proposed work has been shown in figure 3.1. The proposed work is very efficient for real life video super resolution.

Steps of Simulation:-

1. Initialize system parameters: The system parameters for image processing such as -Database of calibrated multispectral image data, Industry-standard test targets and image quality metrics, Design and analysis of scene and optical parameters, Design and analysis of pixel and sensor parameters, Intuitive, point-and-click interface, Open programming interface for proprietary algorithms

2. Browse degraded low resolution test video sequence to be enhanced as high resolution video.

3. Start reading video frames from browsed video sequence.

4. Separate video frames from browsed low resolution test video.

5. Convert Frame in to Ycbcr color space: Convert separated frames in to Ycbr color space n Matlab

$$RGB = imread('peppers.png');$$

$$YCBCR = rgb2ycbcr(RGB);$$

6. Apply Mask Defined: Apply defined mask to YCbCr colour space converted frames.

7. Adding Motion Blur & Gaussian noise: Add Motion blur and Gaussian noise in to test frames.

8. Save Blurred and Noise Frames: Save blurred and noisy frames.

9. Apply recursive integration scheme on noisy frames

10. Apply Radial Sharpening for information refinement

11. Save reconstructed video sequence

12. Calculate PSNR of reconstructed video sequence

13. Display Input degraded and reconstructed video sequence : display input degraded and reconstructed video sequence.

IV. SIMULATION RESULT

The implementation of proposed work is performed on MATLAB environment. The proposed methodology contains recursive approach to estimate integration parameters of the blocks of video frames. Each frame is processed with the inclusion of Gaussian noise and motion blur to create the degraded video sequence the noise density and motion blur ratio is same as taken in the existing work. After that the recursive estimation approach is applied to reconstruct the video sequence. The comparison of proposed work with existing super-resolution technique shows that state of art of the proposed work is better with respect to existing techniques for super-resolution. Figure 4.1 show the experiment outcome of proposed work for a Original video sequence of BUS (a) Input Video, (b) Degraded Video and (c) Reconstructed Video.

Second experiment has performed on Original video sequence of CITY (a) Input Video, (b) Degraded Video and (c) Reconstructed Video as shown in figure 4.2.

(a) (b) (c)

Figure 4.1: Original video sequence of BUS (a) Input Video, (b) Degraded Video and (c) Reconstructed Video.

(a) (b) (c)

Figure 4.2: Original video sequence of CITY (a) Input Video, (b) Degraded Video and (c) Reconstructed Video.

In input video there may be different types of degradation like fog, blurness which have to estimate for enhancement. our proposed algorithm is considered for three types of degradations.

Motion estimation in the degraded video is done due to process the finest elements present in an image which are finest that blur also.

Image has been converted in RGB format to YCbCr format and applied upsampling to Cb and Cr plane but the intensity plane Y is upsampled.

Figure 4.3 shows the third experiment on Original video sequence of MOBILE (a) Input Video, (b) Degraded Video and (c) Reconstructed Video.

(a) (b) (c)

Figure 4.3: Original video sequence of MOBILE (a) Input Video, (b) Degraded Video and (c) Reconstructed Video.

Video is considered as sequence of frames and applied proposed work on degraded video sequence to estimate blur and to remove it. The evaluated results obtained from the experiment of proposed work have shown in table 1. The estimation of blur has done by multiscale process but before that to upsample the frames with the help of non-uniform interpolation super-resolution is required. The graphical representation of performance comparison of proposed work with existing work has given in figure 4.4.

Table 1: PSNR Comparison with Proposed and Existing methods.

Reconstruction Techniques	***City***	***Bus***	***Mobile***
Existing Method	35.7 dB	28.70 dB	26.60 dB
Proposed Methods	**42.86 dB**	**34.6 dB**	**32.00 dB**

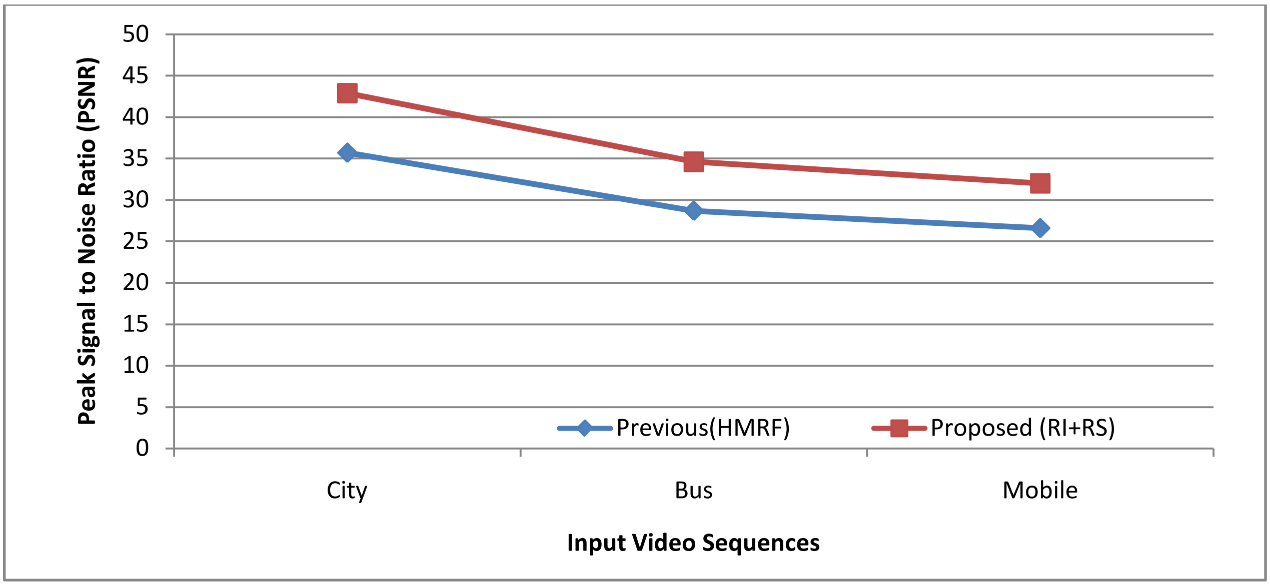

Figure 4.4 PSNR comparison chart.

V. CONCLUSION

In these work different scenarios for video super-resolution has been examined. The multiple low-resolution cameras utilization has been examined, instead of one, may enhance the super-resolution process. The algorithm for development of robust video super resolution restoration using recursive integration and radial sharpening has been proposed for exploiting low quality low resolution video frame. In this work a Low quality low resolution video sequence has been taken in Matlab environment and enhanced resolution using proposed super resolution approach. PSNR for different video sequence has been calculated and compared with existing approach it is concludes that proposed work has better results as compared to existing approach. Although, the algorithm cannot perform as well for the sequences containing fast motions, but it is designed to enhance the spatial resolution of decoded multi-view video sequence. This problem remains as a future work has may be done later in the direction to enhance the performance of the multi-view video super-resolution algorithm using recursive integration and radial sharpening.

REFERENCES

[1] E. Faramarzi, D. Rajan, F. C. A. Fernandes and M. P. Christensen, "Blind Super Resolution of Real-Life Video Sequences," in IEEE Transactions on Image Processing, vol. 25, no. 4, pp. 1544-1555, April 2016.

[2] J. Jiang, X. Ma, Z. Cai and R. Hu, "Sparse Support Regression for Image Super-Resolution," in IEEE Photonics Journal, vol. 7, no. 5, pp. 1-11, Oct. 2015.

[3] C. Yang, J. Wang, A. Stern, S. Gao, V. Gurev and B. Javidi, "Three-Dimensional Super Resolution Reconstruction by Integral Imaging," in Journal of Display Technology, vol. 11, no. 11, pp. 947-952, Nov. 2015.

[4] Y. Chen, Y. Ge, G. B. M. Heuvelink, J. Hu and Y. Jiang, "Hybrid Constraints of Pure and Mixed Pixels for Soft-Then-Hard Super-Resolution Mapping With Multiple Shifted Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 8, no. 5, pp. 2040-2052, May 2015.

[5] Xiaole Yan, Qiu Shen and Xin Liu, "Super-resolution reconstruction for license plate image in video surveillance system," 2015 10th International Conference on Communications and Networking in China (ChinaCom), Shanghai, 2015, pp. 643-647.

[6] S. Gohshi, "Real-time Super Resolution equipment for 8K video," 2014 International Conference on Signal Processing and Multimedia Applications (SIGMAP), Vienna, 2014, pp. 149-156.

[7] S. Gou, S. Liu, S. Yang and L. Jiao, "Remote Sensing Image Super-Resolution Reconstruction Based on Nonlocal Pairwise Dictionaries and Double Regularization," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 7, no. 12, pp. 4784-4792, Dec. 2014.

[8] S. Borman and R. L. Stevenson, “Spatial resolution enhancement of low- resolution image sequences: A comprehensive review with directions for future

research," Dept. Elect. Eng., Univ. Notre Dame, Notre Dame, IN, USA, Tech. Rep., Jul. 1998.

[9] S. Borman and R. L. Stevenson, "Super-resolution from image sequences A review," in Proc. Midwest Symp. Circuits Syst., Notre Dame, IN, USA, Aug. 1998, pp. 374-378.

[10] S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: A technical overview," IEEE Signal Process. Mag., vol. 20, no. 3, pp. 21-36, May 2003.

[11] R. R. Schultz, L. Meng, and R. L. Stevenson, "Subpixel motion estimation for super-resolution image sequence enhancement," J. Vis. Commun. Image Represent., vol. 9, no. 1, pp. 38-50, Mar. 1998.

[12] A. M. Tekalp, Digital Video Processing (Prentice Hall Signal Processing Series). Englewood Cliffs, NJ, USA: Prentice-Hall, 1995.

[13] Y. Caspi and M. Irani, "Spatio-temporal alignment of sequences," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 11, pp. 1409-1424, Nov. 2002.

[14] O. Shahar, A. Faktor, and M. Irani, "Space-time super-resolution from a single video," in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2011, pp. 3353-3360.

[15] V. Cheung, B. J. Frey, and N. Jojic, "Video epitomes," Int. J. Comput. Vis., vol. 76, no. 2, pp. 141-152, 2008.

[16] [9] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," ACM Trans. Graph., vol. 25, no. 3, pp. 787-794, 2006.

[17] Q. Shan, J. Jia, and A. Agarwala, "High-quality motion deblurring from a single image," ACM Trans. Graph., vol. 27, no. 3, p. 73, 2008.

[18] S. Cho and S. Lee, "Fast motion deblurring," ACM Trans. Graph., vol. 28, no. 5, 2009, Art. ID 145.