Efficient Real Life Video Sequence Restoration using Recursive Compound Scheme

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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-researched subject. 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 problem now a days due to huge usage and availability digital cameras. To overcome low resolution issue in real life video sequences an efficient Video Sequence Restoration scheme based on Recursive Compound has been proposed in this work. Implementation and simulation of proposed work has been done on Matlab and Isim simulator.

Keywords - Video Reconstruction, Recursive Compound, 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. As a result, the image sensor size should be increased, that increases the size of optics used in the device.

The problem of enhancing each frame of a low-resolution video sequence by exploiting 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.

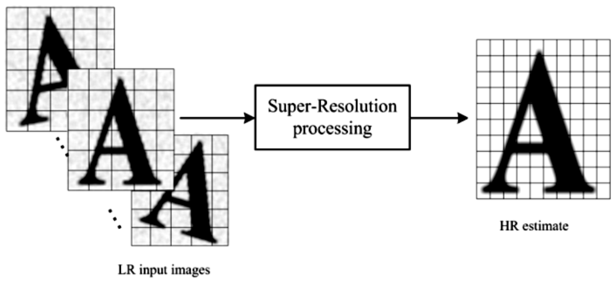


Figure 1.1 Illustration of super-resolution inverse problem: Given a number of low resolution frames of the same scene, construct a single frame with an improved resolution.

Super resolution (SR) reconstruction refers to the process of combining a sequence of under-sampled and degraded low-resolution (LR) images in order to produce a single high-resolution (HR) image. The LR input images are assumed to portray slightly different views of the same scene. In broad sense, super-resolution techniques attempt to improve the spatial resolution by incorporating into the final result the additional new details that are revealed in each LR image. Conceptually, the processing allows to convert the temporal resolution into spatial resolution.

The basic assumption for super-resolution processing is that some LR images contain novel and non-redundant information about the scene details. This may be due to relative camera motion from one frame to another, possibly resulting from the combination of camera motion, moving objects in the scene, camera jitters, shaking, etc. In order to apply super-resolution, it is important to extract the relative displacement of the portrayed details at sub-pixel precision.

The fundamental problem that is addressed in super-resolution is a typical ex- ample of an ill-posed inverse problem wherein the original information (HR image) is estimated from the degraded observations (LR images). To solve for the inverse problem, explicit regularization strategies need to be incorporated in order to constrain the feasible solution space. The redundant information in the input LR images is inherently utilized in the solution to regularize the inverse problem and improve the final solution. Obviously, to obtain a meaningful solution of the inverse problem, it is critical to employ realistic modeling of the imaging process.

II. SYSTEM MODEL

Given a set of low-resolution images that result from the observation of the same scene from slightly different views, super-resolution algorithms produce a single high resolution image by fusing the input LR images such that the final HR image reproduces the scene with a better fidelity than any of the LR images. The central idea in super-resolution processing is to convert the temporal resolution.

into spatial resolution. In broad sense, this approach can be used to perform any combination of the following image processing tasks:

- Interpolation
- Denoising
- Deblurring

Usually, super resolution methods consist of the following basic processing steps:

- Motion estimation to determine the relative shifts between the LR images and register the pixels from all available LR images onto a common refer- ence grid. This step is essential to enable motion compensated filtering.
- Motion compensation and warping of the input LR images onto the refer- ence grid. Note that the pixels of the LR images are usually non-uniformly distributed with respect to the reference grid.
- Restoration of the LR images in order to reduce the artifacts due to blurring and sensor noise. The filtering is necessary to improve the perceived image quality.
- Interpolation of the LR images with a predetermined zoom factor to obtain the desired HR size.
- Fusing of the pixel values from the LR images. This temporal filtering operation is at the heart of all super-resolution algorithms, and complements the spatial filtering operations performed in the previous steps.

Fig. 2.1 illustrates the generic processing steps described above. It is important to note that in some algorithms, the order of the operations might be different. In the following chapter, different known approaches for super-resolution are presented and discussed in more detail.

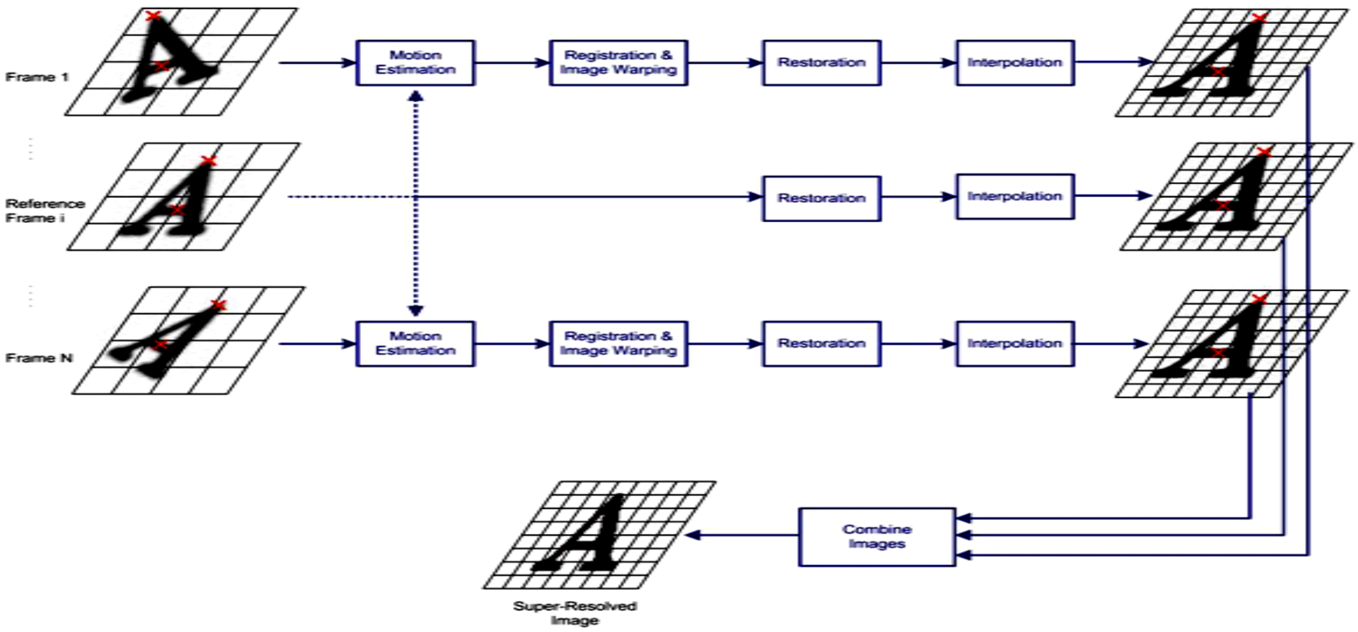


Figure 2.1 Schematic of an basic example. Several complex processing steps are integrated in super-resolution.

III. PROPOSED METHODOLOGY

Proposed work for low resolution real life video sequence based on restoration using recursive compound scheme has been shown in figure 3.1. there are the following steps in flow of proposed work listed below. The implementation of proposed work has done on Matlab Ra2011.

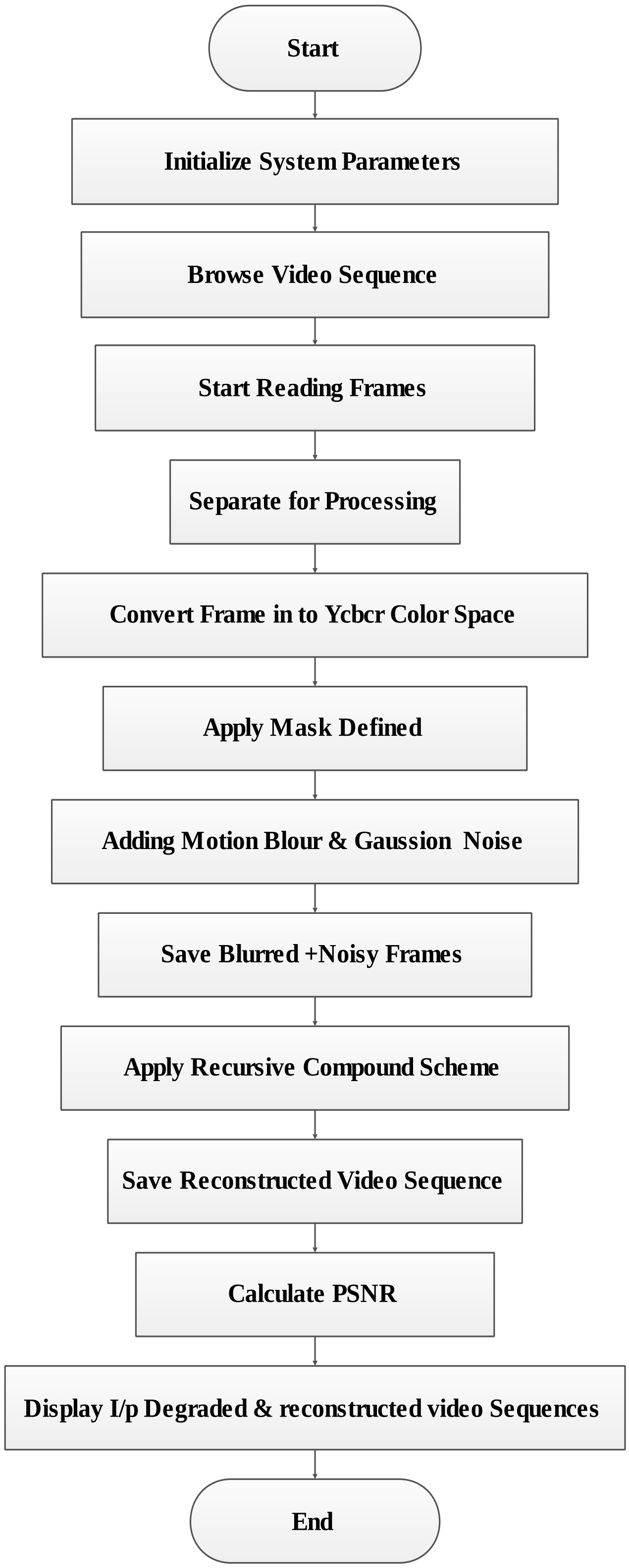


Figure 3.1 Flow Chart of Proposed Work.

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 Video Sequence : Browse degraded low resolution test video sequence to be enhanced as high resolution video.

3. Start Reading Frames: Start reading video frames from browsed video sequence.

4. Separate for Processing : 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 Compound Scheme: Apply recursive compound scheme on noisy frames

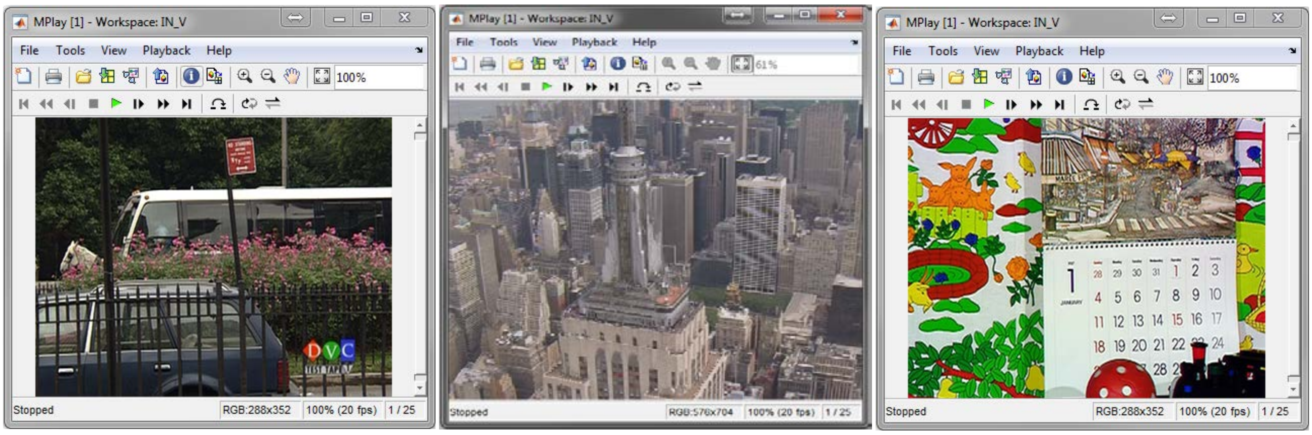
10. Save reconstructed video sequence: Save the reconstructed video sequence

11. Calculate PSNR: Calculate PSNR of reconstructed video sequence

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

IV. EXPERIMENTAL RESULTS

The proposed work is shown by MATLAB implementation. The proposed methodology contains recursive approach to estimate compounds 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 are have same as taken in the existing work. After that the compound estimation approach is applied to reconstruct the video sequence. We have compared proposed work with existing super-resolution technique and shown that state of art of the proposed work is better compare to existing techniques for super-resolution.



(a) (b) (c)

Figure 4.1: Original video sequence of (a) BUS, (b) CITY and (c) Mobile as an input to system.

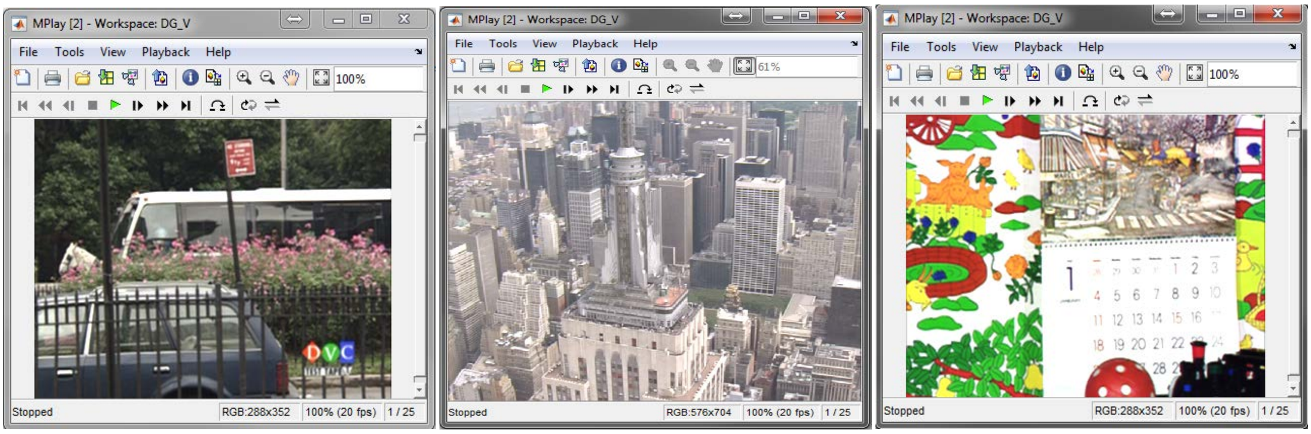


Figure 4.2: Degraded video sequence of (a) BUS, (b) CITY and (c) Mobile as an input for estimation and reconstruction process.

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

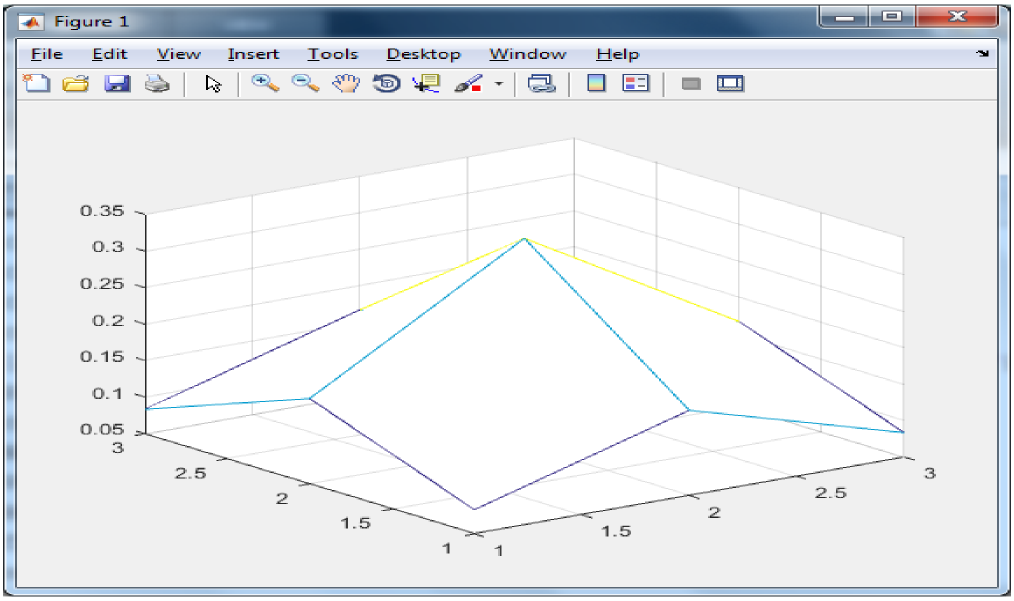


Figure 4.3: Motion Estimation in Video Sequence

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

We converted Image which is in RGB format to YCbCr format and normally we applied upsampling to Cb and Cr plane but the intensity plane Y is upsampled.

Figure 4.4: Proposed method (recursive compound) of (a) BUS, (b) CITY and (c) Mobile video Sequence.

Video is considered as sequence of frames and we applied proposed work on degraded video sequence to estimate blur and to remove it. So finally we got these results. We estimated the blur by multiscale process but before that we have to upsample the frames with the help of nonuniform interpolation super-resolution.

Table 1: PSNR Comparison with Proposed and Existing methods

SR Methods	***City***	***Bus***	***Mobile***
Existing Method	35.7 dB	28.70 dB	26.60 dB
Proposed Methods	**49.61 dB**	**42.75 dB**	**39.81 dB**

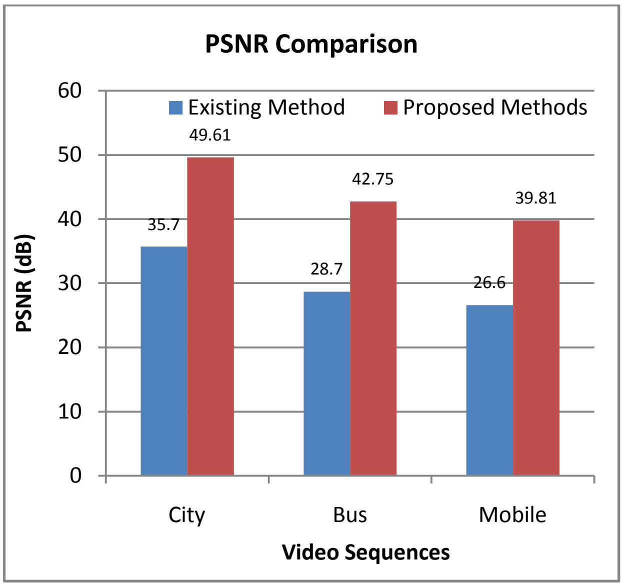


Figure 4.5 PSNR comparison chart

V. CONCLUSION AND FUTURE SCOPES

Super-resolution reconstruction consists in the process of creating a high resolution image from a sequence of low resolution images. In the context of low-end consumer imaging products, this filtering technique has the potential to make significant economies of scale since it proposes to overcome the intrinsic hardware limitations by using the available computational resources. This work present an efficient real life video sequence restoration using recursive compound scheme. Implementation of proposed work has done on Matlab and simulated on Isim Matalb simulator. The result obtained are compared with existing work [1] in terms of PSNR. The performance evaluated of proposed work is better as compared to existing work. In future proposed system can be implemented for real-time camera video sequences.

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