Improvement in Video Resolution Using Bayesian Algorithm

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Abstract
Videos with super resolution quality are giving its credit to the medical and military fraternity. One such approach is to improve the video quality from high resolution to super resolution (SR). Simply this can be done by using interpolation techniques such as nearest neighbourhood and Bilinear method. But for more appropriate reconstruction, the proposed method can be used. The principle step for it is based on Bayes theorem and an approximation of symmetric alpha-stable (SαS). It performs maximum a posterior (MAP) estimation of reconstructed high resolution (HR) image. The heavy tails of the distribution of high resolution image can be captured by the proposed algorithm and hence the edges of the reconstructed image can be preserved in better way. It removes the noise from digital images, while the visual quality of the image is preserved very well. If the received image is in good quality then automatically the video quality will also improve.

Keywords
Super Resolution; Nearest neighborhood method; Bilinear method; Alpha-stable distributions and Bayesian Algorithm.

I. Introduction
High Resolution (HR) images are at all times essential and requisite in many military and civilian applications. HR can be defined as number of pixels within a given size of image and is large in quantity. Therefore, for a variety of practical applications an HR image gives critical information. Petroleum exploration, remote sensing, medical imaging, data mining, military information gathering and high definition television (HDTV) are the areas where it can be widely used [3].

To enhance the resolution, there is imperative need for developing post-acquisition signal processing techniques. These techniques offer flexibility and there is no additional hardware involved, so adds cost benefice. However, a user has to suffer an increased computational cost that may be the burden. This resolution enhancement is called super- resolution (SR) image reconstruction. In SR reconstruction, an HR image is restored by using a video sequence or several LR images. By using optical devices, noises are eliminated and blurs. The size is limited by using embedded sensor chips. To increase the resolution of a sequence of degraded images has engrossed extensive attention of researchers in the field of computer vision and machine learning.
This paper is organized section wise and is as follows: In Section II, all preliminary works are mentioned. Section III deals with two approaches of reconstruction: Nearest neighborhood and Bilinear method. Section IV gives the information about the alpha-stable distribution and Section V is about Bayesian algorithm. Finally, Section VI produces all the results and discussions related to it.

II. Literature Survey
In the last few decades, our lifestyle has changed enormously due to the development of the image and video technology. This has made many popular SR reconstruction algorithms which can be roughly divided into two categories:

1. Frequency domain algorithms and
2. Spatial domain algorithms.

Tsai and Huang [4] proposed the first work for the SR reconstruction by estimating the relative shifts between observations. Their approach is called frequency domain algorithms and is based on the following three aspects: the property of shifting of Fourier transform, the spectral aliasing principle, and the limited bandwidth of the original HR image. Based on this algorithm, a series of improved SR reconstruction algorithms had been proposed [5-6].

For spatial domain algorithms started with non-uniform interpolation-based approach whose computational cost is relatively low so they are ready for real-time applications. However, degradation models are not applicable in these approaches if the blur and the noise characteristics are different for LR images. Projections on a convex set (POCS) based methods have common advantage of simplicity, i.e., the utilization of the spatial domain observation model and inclusion of a priori information. However, their disadvantages are non-uniqueness of solutions, slow convergence rate and heavy computational load. Iterative back projection (IBP) based approaches conduct SR reconstruction in a straightforward way.

Christopher R. Dance and Ercan E. Kuruoglu proposed that stable distribution has proved to be strong alternatives to the Gaussian distribution. Most of the real life signals are skewed. Closed form estimates that characteristic function techniques yield the parameters which may be efficiently computed. Weighted sums of stable variates can be applied to find the skew and location parameters. [3] An important property of Gaussian Random Variable is that the sum of two of them is itself a Normal Random Variable.

Jin Chen, Jose Nunez-Yanez, and Alin Achim investigated the increasing problem of spatial resolution of video frames. It is done by using three prior models: GMRF (Gaussian Markov Random Field), BTV (Bilateral Total Variation) and GGMRF (Generalised Gaussian Markov Random Field). GGMRF preserves sharp edges of image in a better way. [4]

Xuelong Li, Yanting Hu, Xinbo Gao, Dacheng Tao and Beijia Ning proposed a new multiframe SR reconstruction algorithm which is based on image local characteristics. Locally adaptive bilateral total variation model is used as regularization parameter to balance noise suppression. It introduces a gradient error which is used as gradient consistent constraint [5].

III. Interpolation Techniques
Super Resolution (SR) technique is method of constructing HR frame from several LR frames. The main idea behind it is to combine the non-redundant information contained in multiple LR Frames to generate a HR image. The closely related technique is single frame interpolation approach. Due to this technique,

the size of the frame increases. But there will be no additional information. Hence the quality of single frame will be very much limited. It cannot be recovered easily because of lost frequency components. Here we took the cases of nearest neighborhood and bilinear method.

The nearest neighborhood method is very simple and requires less computation as it use nearest neighbor's pixel to fill interpolated point. This method is just copies available values, not interpolate values as it doesn't change values.

In bilinear method, interpolated point is filled with four closest pixel's weighted average. In this method we performed two linear interpolations, in horizontal direction and then linear interpolation in vertical direction. It is required to calculate four interpolation functions for grid point in Bilinear Interpolation. It is used to know values at random position from the weighted average of the four closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The two linear interpolations are performed in one direction and next linear interpolation is performed in the perpendicular direction.

Consider an image of size 2X2 and is in figure 1.

2	3
4	5

Fig. 1: 2X2 Image

As per nearest neighborhood technique, the new image is shown in figure 2.

2	2	3	3
2	2	3	3
4	4	5	5
4	4	5	5

Fig. 2: Nearest Neighborhood Image

With filler the bilinear method image will turns into an image as shown in figure 3.

2	F	3	F
F	F	F	F
4	F	5	F
F	F	F	F

Fig. 3: Transformed Image

Thus for every F, calculate the mean of the surrounding pixels. Eventually, you will be able to calculate the mean for every F, even those that were originally surrounded by all F.

2	F	3
F	F	F
4	F	5

Fig. 4: Bilinear Image

Eventually, the middle F in fig. 4 should calculate out to being (2+3+4+5)/4=14/4.

IV. Alpha-Stable Distributions

New statistical approach will deal with alpha-stable model which will be used as learning model. Stable distributions are a rich class of probability distribution that allow skewness and heavy tails and have many interesting mathematical properties. Stable distributions have been proposed as a model for many types of physical and economic systems. It is also used to characterize wavelet coefficients of natural images. Since the wavelet coefficients are symmetric in nature, it should be modeled first. Therefore we restrict our self to the case of symmetric alpha-stable distributions.

A general alpha-stable distribution is specified as S (α, β, c,δ). It is determined using four parameters.

The four parameters are as follows:

1. Shape parameter α (also known as characteristic exponent).
   - Most important parameter of a stable distribution.
   - The smaller the characteristic exponent α, heavier the tails of the SαS density
2. Skewness parameter β is in $[-1, 1]$ and measures the asymmetry of the distribution.
3. Scale parameter, c indicates the width
4. Location parameter δ indicates the location of the distribution.

Characteristic function of one-dimensional α-stable distributions can be described as in equation 1:

$$\Phi(z) = \exp(-c|z|^{\alpha}[1 + j\beta\,\mathrm{sign}(z)\tan(\tfrac{\alpha\pi}{2})] + j\delta \qquad (1)$$

for characteristic exponent $\alpha \in (0, 1) \cup (1, 2)$, symmetry parameter (skew) $\beta \in [-1, 1]$, dispersion $c > 0$ and location parameter $\delta \in (-1, 1)$. Do not consider the cases $\alpha = 1, 2$ where the distribution has special behaviour. Such α-stable distributions have proved to be strong alternatives to the Gaussian distribution.

A. Univariate Symmetric Alpha-Stable Distributions

The two main theoretical reasons for alpha-stable distributions to be used as a statistical model are:

1. Stable random variables satisfy the stability property. Stability property states that the linear combinations of jointly stable variables are indeed stable. Stability is nothing but the shape of the distribution remains unchanged (or stable) under such linear combinations.
2. Stable processes arise as limiting processes of sums of independent identically distributed (i.i.d.) random variables using the generalized central limit theorem. The distribution lacks a compact analytical expression for its probability density function (pdf).

Consequently, it is most conveniently represented by its characteristic function as given in equation (2):

$$\Phi(z) = \exp(-c\,|z|^{\alpha} + j\,\mu\,z) \qquad (2)$$

where α is taking values $0 < \alpha \leq 2$, $-\infty < \mu < \infty$ and $c > 0$ for the above the distribution. The characteristic exponent (α) is the most important parameter of the SαS distribution, as it determines the shape of the distribution. For values of α in the interval (1-2], the location parameter μ corresponds to the mean of the distribution, while for $0 < \alpha \leq 1$, μ corresponds to its median. The dispersion parameter (c) determines the spread of the distribution around its location parameter, similar to variance of Gaussian distribution [1].

B. Bivariate Stable Distributions

Bivariate stable distributions are characterized by the stability property and the generalized central limit theorem same as that of univariate stable distributions. Bivariate stable distribution is distinct from univariate stable distribution by a single reason. It forms a nonparametric set, therefore, more difficult to describe. Characteristic function for bivariate stable distributions can be stated in equation (3) and is as follows:

$$\Phi\,(z_1, z_2) = \exp\,(-c\,|z|^{\alpha} + j\,(\mu_1 z_1 + \mu_2 z_2)) \qquad (3)$$

The distribution is isotropic with respect to the location point (z_1, z_2). The two marginal distributions of the isotropic stable distribution are with parameters (z_1, c, α) and (z_1, c, α). Bivariate isotropic Cauchy and Gaussian distributions are special cases and can be represented as $\alpha = 1$ and $\alpha = 2$ respectively.

The bivariate pdf in these two cases are given in equation (4).

$$P_{\alpha,c}(x_1, x_2) = \frac{c}{2\pi(x_1{}^2 + x_2{}^2 + c^2)^{\frac{3}{2}}} \quad \text{for } \alpha = 1$$
$$= \frac{1}{4\pi c}\exp\left(-\frac{x_1{}^2 + x_2{}^2}{4c}\right) \quad \text{for } \alpha = 2 \qquad (4)$$

As in the case of the univariate density function, when $\alpha \neq 1$ and $\alpha \neq 2$, no closed-form expressions exist for the density function of the bivariate stable random variable [1].

V. Bayesian Algorithm

The proposed algorithm transforms the input video to newly reconstructed video. The flowchart as shown in fig. 5 gives the generalized idea behind the algorithm.

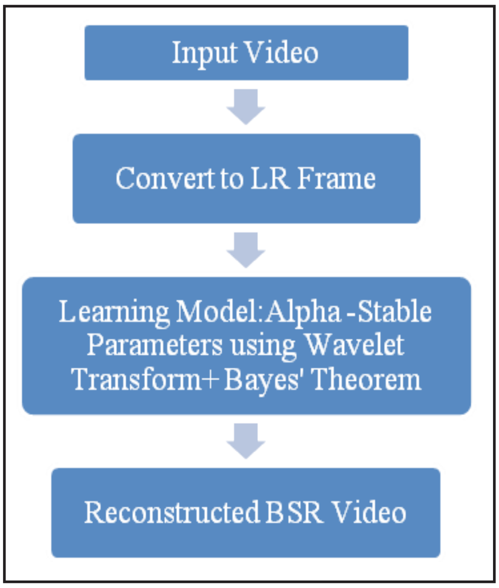

Fig. 5: Flowchart of Proposed Algorithm

Classical three-step technique can be used for video reconstruction using Bayesian method:

1. Convert the true frames to Low Resolution (LR) frames.
2. Learning model will be designed.
3. Apply Bayes' theorem.

A. Bayes Theorem Implementation

The wavelet transform is a linear operation. After decomposing an image into six sub-bands consequently and for every two adjacent levels, sets of noisy wavelet coefficients represented as the sum of the transformations of the signal and the noise [2] are given as in equation (5).

$$y_j = x_j + n_j$$
$$y_{j+1} = x_{j+1} + n_{j+1} \qquad (5)$$

where $1 < j < J$ refers to the decomposition level.

Equation (6) is the vectorial form of above set of equations and can be written as

$$y = x + n \qquad (6)$$

where $y = (y_j, y_{j+1})$, $x = (x_j, x_{j+1})$, $n = (n_j, n_{j+1})$.

The MAP estimator of given image, the noise observation can be easily derived as follows:

$$X = \operatorname{argmax}_X P_{x/y}\, P\left(\frac{x}{y}\right) \qquad (7)$$

Using Bayes' theorem, equation (7) can be written as:

$$X = \operatorname{argmax}_X\; P_n(y - x) P_x(x)$$
$$\operatorname{argmax}_X\; P_n(n) P_x(x) \qquad (8)$$

Additionally, the shrinkage of a coefficient is also conditioned using equation 8. The shrinkage is done on the value of the corresponding coefficient at the next decomposition level (parent value); the smaller the parent value, the greater the shrinkage [1].

B. Estimation of Parameters

The reconstructed frame can be estimated using the parameters such as PSNR and SSIM. Peak Signal to Noise Ratio (PSNR) widely used for measuring the quality of reconstructed image. Logarithmic scale is used for measuring PSNR. It is defined as ratio of maximum possible power of image data and power of noise is the error introduced by compression that affects the fidelity of its representation.

Usually high PSNR represents high quality of reconstructed image while low PSNR represents low quality of reconstructed image. It is calculated as written in equation 9:

$$\text{PSNR} = 10\log_{10}\left(\frac{\text{Max}_I{}^2}{\text{MSE}}\right) \qquad (9)$$

where Max_I is the maximum possible pixel value of frame.

Apart from measuring the PSNR, the structural similarity (SSIM) is also used to measure the reconstruction quality [1]. Compared with the more traditional PSNR, SSIM has been proven to be more consistent with human eye perception. The SSIM is given in equation 10.

$$\text{SSIM} = \frac{(2\mu_a\mu_b + c_1)(2\delta_{ab} + c_2)}{(\mu_a{}^2 + \mu_b{}^2 + c_1)(\delta_a{}^2 + \delta_b{}^2 + c_2)} \qquad (10)$$

where μ_a and μ_b are the mean values, δ_a and δ_b are their variances, and δ_{ab} is the covariance. $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$ are two variables used to stabilize the division with weak denominator, where L is the dynamic range of the pixel values and $k_1 = 0.01$, $k_2 = 0.03$ by default. The SSIM measure should be close to unity for an optimal effect of SR reconstruction [1].

VI. Results and Conclusion

Here the video taken is rhinos.avi as an input and the algorithms used are: Nearest Neighborhood method, Bilinear method and Bayesian Super Resolution method.

Fig. 6 shows how the true frame is constructed to low resolution frame. By using the interpolation techniques, the changes in the frame are low and medium for nearest neighborhood, bilinear method and Bayesian Super Resolution respectively. For 10 iterations, the frames can be resolved as super-resolution frame. Fig. 7 shows the super-resolved frame of true frame in figure 7 with ×3 zoom factor. For every the PSNR value is increasing and RMSE is decreasing. This indicates that the quality of image is improving. With the increase in number of iterations, the reconstruction will be very good and automatically the frame quality will increase.

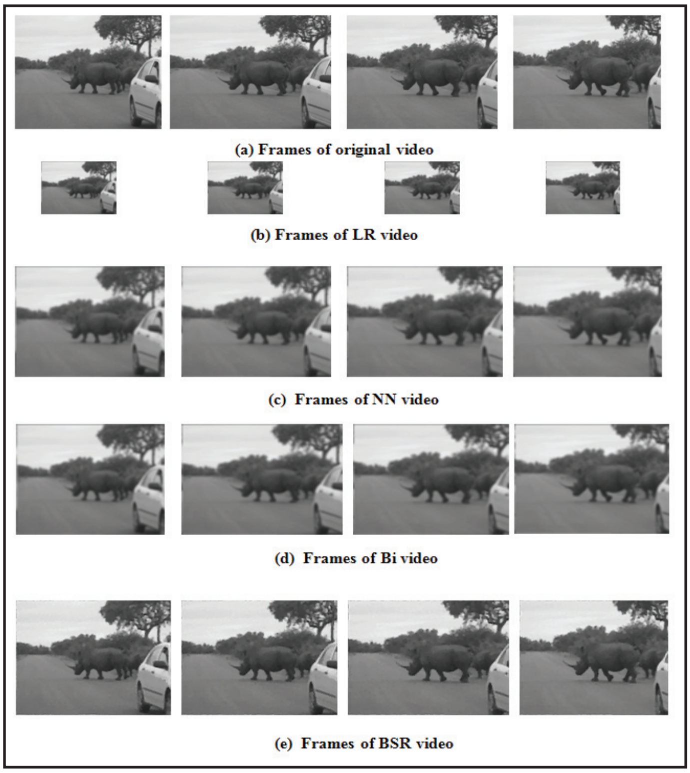

Fig. 6: Results of Interpolation and Proposed Algorithms

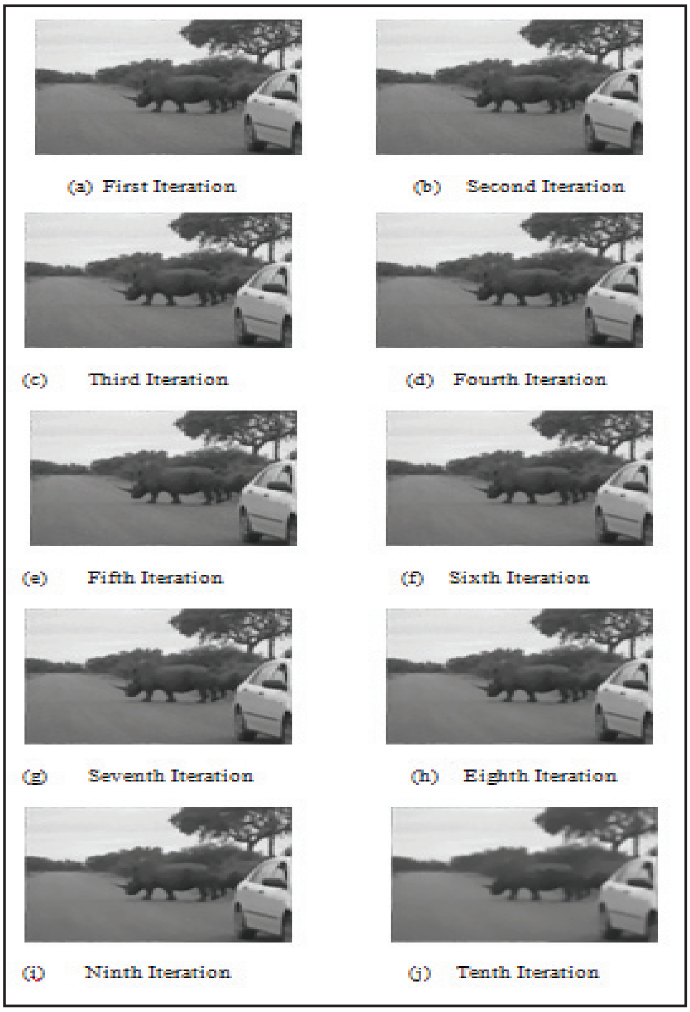

Fig. 7: Result of Bayesian Algorithm with iteration as 10

The below given plots are the actual graphs obtained while MATLAB processing. Fig. 8 shows the PSNR plot for Nearest Neighborhood (NN) (Red in color), Bilinear (BI) (Blue in color) and Bayesian Super Resolution Algorithm (BSR) (Green in color). The plot shows that the PSNR value of proposed method is the highest among the other two methods. This indicates the quality of video of proposed method is relatively good than the nearest neighbourhood method and bilinear method. The maximum value is 32.80dB.

Fig. 9 shows the SSIM plot for Nearest Neighbourhood (Red in color), Bilinear (Blue in color) and Bayesian Super Resolution Algorithm (Green in color).

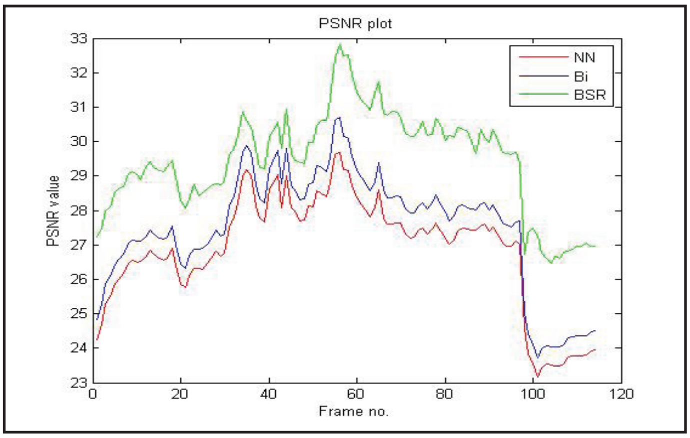

Fig. 8: Plot of PSNR for rhinos.avi

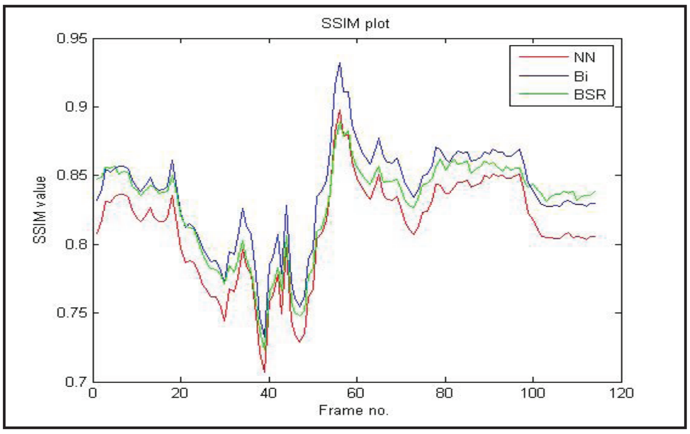

Fig. 9: Plot of SSIM for rhinos.avi

From the above discussions and from Table 1, we can conclude that Bayesian approach is giving reliable result than interpolation technique. The plus points of proposed methodology is Low Resolution system scan be used as it is.

The heavy tails of the distribution of high resolution image can be captured in better way. The edges of the reconstructed image can be preserved in better way and it easily improves the video quality.

Table 1: Analysis of all the Three Methods

Sr. No.	Method	PSNR	SSIM	Quality
1.	NN	LESS	LESS	LOW
2.	BI	MEDIUM	MEDIUM	MEDIUM
3.	BSR	HIGH	HIGH	GOOD

The disadvantages of this approach are that there should be detailed information about the priors and time consumption is very huge in amount.

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In future, there is an idea to develop a Bayesian approach to joint super-resolution and fusion of video sequences acquired with different modalities.

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