

ABSTRACT

Several competing methodologies are emerging in the field of video processing regarding the super-resolution (SR) restoration of video sequences. The narrowly associated problem of erection of SR still images from image sequence is taken into consideration. This paper discusses on the states the art of SR techniques using a classification of existing techniques such as frequency domain algorithms and spatial domain algorithms. This will identify the areas which will promise the performance parameter.

Keywords: Super-resolution (SR) restoration; Frequency domain algorithms; Spatial domain algorithms; SR techniques

INTRODUCTION

In the last few decades, development of the image and video technology has changed our lifestyle enormously. This has made many popular super-resolution (SR) reconstruction algorithms. In traditional single image restoration, only a single input image is accessible. The mission of obtaining a super resolved image from an under-sampled and degraded image sequence can lead to the supplementary spatiotemporal data obtainable in the image sequence. Similar but no identical information is there in data available in the camera and this scene motion lead to frames in the video sequence.

The problem of resolution enhanced stills from a sequence of low resolution (LR) images of a translate scene is taken into consideration in the work by Tsai and Huang [1]. Inclusion of a-priori constraints enables the reconstruction of a super resolved image with wider bandwidth than that of any of the individual LR frames. Researchers who are working in this domain states the problem of producing SR still images from a video sequence. Here several LR frames are combined to produce a single SR frame.

These techniques may be applied to video restoration by computing successive SR frames from a “sliding window” of LR frames. Constraints such as smoothness are critical to achieving high quality SR reconstructions.

SR reconstruction algorithms which can be roughly divided into two categories:

- I. Frequency domain algorithms and
- II. Spatial domain algorithms.

Figure 1 shows the flow of the paper and the algorithms which are taken into consideration.

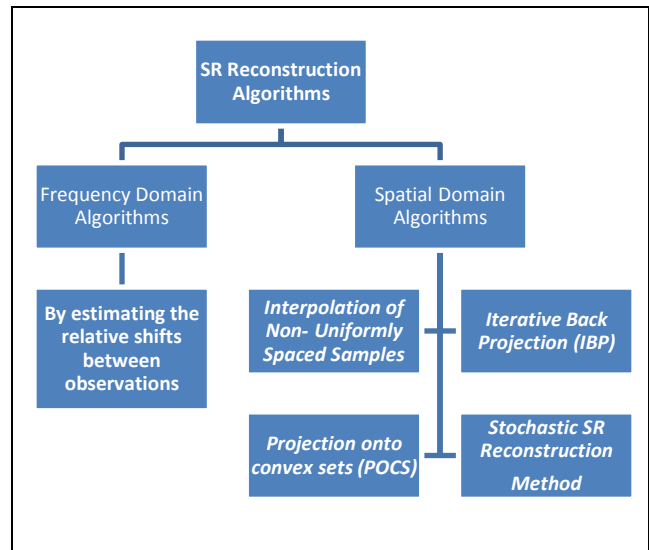


Fig. 1: SR Reconstruction Algorithm's Approach

Section II deals with the frequency domain algorithms and Section III deals with various approaches of spatial domain algorithms. Section IV enlightens about the new way for the generation of SR video sequences. Section V gives the comparison between both the domains.

FREQUENCY DOMAIN METHODS

For frequency domain algorithms, Tsai and Huang [1] proposed the first work for the SR reconstruction by estimating the relative shifts between observations. Their approach is based on the following three aspects:

- Property of shifting of Fourier transform,
- Spectral aliasing principle, and
- Limited bandwidth of the original HR image.

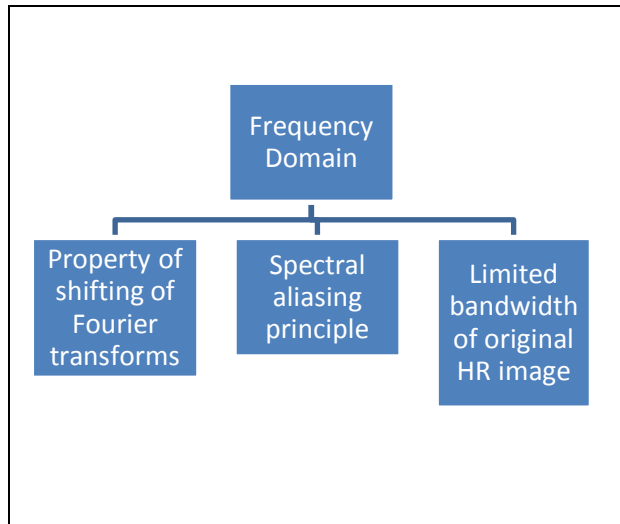


Fig. 2: Frequency Domain Approach

Based on this algorithm, a series of improved SR reconstruction algorithms had been proposed. A system of equations is formulated from the above properties relating the aliased DFT coefficients of the observed images to samples of the CFT of the unknown scene. By solving the equations, the frequency domain coefficients of the original scene can be obtained. It may be then recovered by inverse DFT. It requires knowledge of the translational motion between frames to sub-pixel accuracy. Each observation image must contribute independent equations, which places restrictions on the inter-frame motion that contributes useful data. In this only translations were taken into considerations and disregarded the blurred image.

Advantages of Frequency domain SR methods is its theoretical simplicity, low computational complexity and exhibit a spontaneous de-aliasing SR mechanism.

Disadvantages include the limitation to global translational motion and space invariant degradation models. It is also limited to the ability for inclusion of spatial domain a-priori knowledge for regularization.

SPATIAL DOMAIN METHODS

In this category of SR reconstruction methods, the formulation of observation model and reconstruction is effected in the spatial domain. It is implemented in the spatial domain but fundamentally the technique is frequency domain method only. It basically relies on the shift property of the Fourier transform to model the translation of the source imagery.

The linear spatial domain observation model can accommodate global and non-global motion, optical blur, motion blur, spatially varying PSF, non-ideal sampling, compression etc. Spatial domain reconstruction allows natural inclusion of (possibly nonlinear) spatial domain a-priori constraints (e.g. Markov random fields or convex sets) which result in bandwidth extrapolation in reconstruction.

For spatial domain algorithms, representative works are given as follows. The common advantage of non-uniform interpolation-based approach is that their 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.

Interpolation of Non -Uniformly Spaced Samples

A set of LR images are registered using motion compensation results and are in a single, dense composite image of non uniformly spaced samples. A SR image may be reconstructed from this composite. Restoration techniques are sometimes applied for degradations. Iterative reconstruction techniques such as Landweber iterations [5] are applied as it is very simple. Since the observed data result from severely under-sampled, spatially averaged areas, the reconstruction step (which typically assumes impulse sampling) is incapable of reconstructing significantly more frequency content than is present in a single LR frame. Degradation models are limited, and no a-priori constraints are used.

Iterative Back Projection (IBP)

Michal Irani and Samuel Peleg [2] state that super resolution is feasible for monochrome as well as color image sequences. It can be computed by

relative displacements and with approximate knowledge of image processing. An iterative algorithm is stated. When this algorithm is applied to a single image without increasing the sampling rate, deblurring is reduced with super resolution.

It works well for both computer-simulated and real images and it converges quickly. For faster hardware implementation, this algorithm can be executed parallel. Non-uniform samples and blur that varies between sample locations can be easily located. This method is applicable to simple uniform motions of translation and rotation of entire image as well as perspective transformation and multiple motions in an image.

Projection onto convex sets (POCS)

Projection onto convex sets (POCS) [4] is basically a method of set theory. This is a very popular method as it is very simple. It utilizes the powerful spatial domain observation model and allows convenient inclusion of a priori information.

In set theoretic methods, the space of SR solution images is basically intersected with a set of constraint sets typically convex in nature. It represents the desirable SR image characteristics such as positivity, smoothness, bounded energy, fidelity to data etc. These characteristics yield to a reduced solution space. POCS refers to an iterative procedure which shows that any point in the given space SR images, locates a point which satisfies all the convex constraint sets.

An alternate set theoretic SR reconstruction method [4], to bind the constraint sets an ellipsoid is used. For the SR estimate, the centroid of this ellipsoid is taken as its reference. Since direct computation of this point is not practical or easily achieved. Therefore an iterative solution method is used.

The advantage of set theoretic SR reconstruction techniques is its simplicity. The disadvantages of this method are non-uniqueness of solution and dependence of the solution. This dependency is based on high computational cost, slow convergence and initial guess. This initial guess matters a lot. Though the bounding ellipsoid method ensures a unique solution, there is no claim for optimal solution.

Stochastic SR Reconstruction Method

Stochastic methods such as Bayesian in particular, treat SR reconstruction as a statistical estimation problem. It rapidly gained eminence as it gives a powerful theoretical framework for the inclusion of a-priori constraints. It is necessary for satisfactory solution of the ill-posed SR inverse

problem. The result or the observed data Y , noise N and SR image z are assumed to be stochastic.

Consider now the stochastic observation equation as:

$$Y = Hz + N \quad (1)$$

The Maximum A-Posteriori (MAP) approach to estimating z seeks the estimate for which the a-posteriori probability is a maximum. Then by applying Bayes theorem in equation 1, it is recognized that the estimation of z is independent of probability of occurrence of Y . Since, the likelihood function is determined by the PDF of the noise.

It is common to utilize Markov random field (MRF) image models as the prior. A distinctive assumption of Gaussian noise to be chosen as the prior is to ensure a convex optimization enabling the use of descent optimization procedures. Examples of the Bayesian methods for SR reconstruction as an application may be found by using a Gaussian MRF and with a Huber MRF. Maximum likelihood (ML) [3] estimation has also been functional to SR reconstruction. When there is no prior term, ML estimation becomes a special case of MAP estimation. Since the inclusion of a-priori information is essential for the solution of ill-posed inverse problems, MAP estimation should be used in place of ML.

A most important factor of the Bayesian framework is the direct inclusion of a-priori constraints in the solution. It is common practice to use MRF as a prior which provides a powerful method for image.

In the last decade, SR methods using the Bayesian frame work have become central to the design of novel SR algorithms. In [6], Liu and Sun proposed an adaptive video super-resolution using Bayesian approach in which the motion parameters are simultaneously updated along with the SR process.

Another up to date technique is presented in [7], which avoids explicit sub-pixel motion estimation and there is a usage of 3-D kernel regression to exploit spatiotemporal dependencies. Bayesian methods include explicit prior constraints on the solution. The main idea is to use prior as a constraint, a distribution that is almost possible to the real distribution of the original scene.

Among Bayesian SR methods, the Gaussian Markov random field (GMRF) [8] is one of the most used priors. Actually, the choice of prior is of crucial importance for edge preservation in SR image reconstruction. Schultz and Stevenson [9] were the first to investigate that non-Gaussian priors can be used to preserve discontinuities. They use the Huber Markov random field, as the Huber function is

quadratic for small values of input, but linear for large values.

Farsiu proposed the bilateral total variation (BTV) as a prior. This method has good noise suppression ability, but the results tend to be blurred. Babacan et al. [10] addressed the super-resolution problem by employing variation in Bayesian analysis. In their research, the motion parameters and the unknown model parameters are estimated simultaneously and the same BTV function is used as by Farsiu.

In [11] the authors adopted the generalized Gaussian as prior owing to the heavy tail property it possesses. The method was able to offer a good enhancement of visual quality of the super-resolved image. Figure 3 shows the priors which are discussed in this section for the Bayesian Framework.

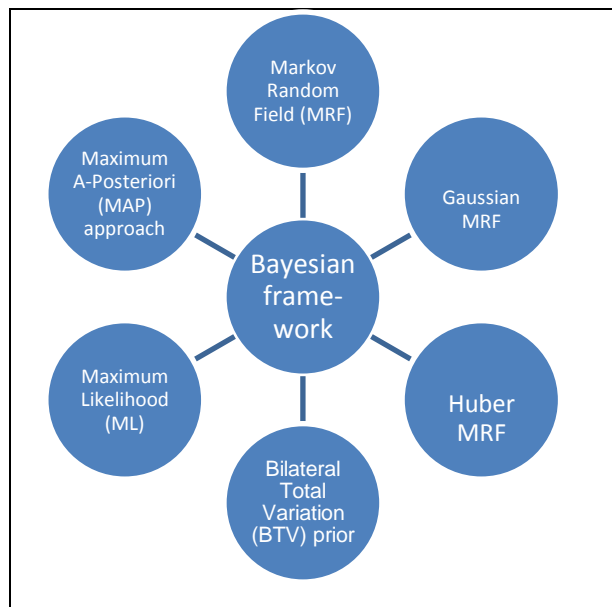


Fig. 3: Bayesian framework Approaches

PROPOSED METHODOLOGY

The various types of existing Bayesian methods, some are discussed in above section have made remarkable progress in the field of super resolution. The future work can be done in this domain using alpha stable distribution as a replacement to Gaussian field. It will act as a Bayesian framework.

Alpha-stable distributions are used to calculate the wavelet coefficients. Bivariate maximum likelihood is an estimator, which relies on the family of alpha-stable distributions. In addition to this Dual-tree complex wavelet transform can be taken in place

of wavelet transform that can improve the directional selectivity.

CONCLUSIONS

A general comparison is done between the two types of domain of SR reconstruction methods with same parameters taken into account which is presented in the below table I.

TABLE I. GENERAL COMPARISON

Sr. No.	DOMAIN CLASSIFICATION & PARAMETERS		
	PARAMETERS	FREQUENCY	SPATIAL
1	Observation model	Frequency	Spatial
2	Motion models	Translational	Almost
3	Degradation	Limited	LSI or LSV
4	SR Mechanism	No priori information	A-priori information
5	Applicability	Limited	Wide

Spatial domain SR reconstruction methods are computationally more complex and more expensive than frequency domain SR reconstruction methods but offers an important advantage in terms of flexibility.

Table II gives the brief discussion about the spatial domain algorithms discussed in the paper. It gives the generalized idea-its advantages and disadvantages.

TABLE II. DISCUSSION ON VARIOUS SPATIAL DOMAIN ALGORITHMS

Sr. No.	SPATIAL DOMAIN ALGORITHMS		
	METHODS	ADVANTAGES	DISADVANTAGES
1	Interpolation of Non - Uniformly Spaced Samples	Simple and for single frame	Degradation models are limited
2	Iterative Back Projection (IBP)	Works well for both computer-simulated and real images Converges quickly For faster hardware implementation →executed	Non-uniform samples and blur are the factors taken into care

Sr. No.	SPATIAL DOMAIN ALGORITHMS		
	METHODS	ADVANTAGES	DISADVANTAGES
		parallel Deblurring is reduced with super resolution without increasing the sampling rate	
3	Projection onto convex sets (POCS)	Simplest and straightforward method	Non-uniqueness of solution Dependence of the solution
4	Stochastic SR Reconstruct ion Method	Treat as a statistical estimation problem Powerful theoretical framework →Inclusion of a-priori constraints	Distinctive assumption required

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