



Multi Image Super Resolution and Blind Deconvolution

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Abstract: A unified blind method for multi-image super-resolution (MISR or SR), single-image blur deconvolution (SIBD), and multi-image blur deconvolution (MIBD) of low-resolution (LR) images degraded by linear space-invariant (LSI) blur, aliasing, and additive white Gaussian noise (AWGN). The better performance blur estimation is done in filter domain rather than pixel domain using gradients of LR and HR images. The Regularization term for blur is Gaussian allowed for fast non iterative optimization in frequency domain. It increases, processing time of SR reconstruction by separating up sampling and registration processes from optimization procedure. The proposed system presented a joint image registration and restoration scheme for both super-resolution and low resolution states of noise, blur, and rough translation motion. To handle global translational motion among low resolution frames. Space-invariant blur, additive white noise and common integer decimation.

Index terms: Blur deconvolution, blind estimation, image restoration, super resolution, Maximum Posterior.

I. INTRODUCTION

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog also are possible.

Image enhancement refers to accentuation, or sharpening, of image features such as boundaries, or contrast to make a graphic display more useful for display & analysis. This process does not increase the inherent information content in data. It includes gray level & contrast manipulation, noise reduction, edge crispening and sharpening, filtering, interpolation and magnification, pseudo coloring, and so on.

Image restoration is concerned with filtering the observed image to minimize the effect of degradations. Effectiveness of image restoration depends on the extent and accuracy of the knowledge of degradation process as well as on filter design. Image restoration differs from image enhancement in that the latter is concerned with more extraction or accentuation of image features.

II. RELATED WORK

In this paper [1], the author describes Forward looking infrared (FLIR) detector arrays generally produce spatially under sampled images because the FLIR arrays cannot be made dense enough to yield a sufficiently high spatial sampling frequency. Multi-frame techniques, such as micro scanning, are an effective means of reducing aliasing and increasing resolution in images produced by staring imaging systems. These techniques involve interlacing a set of image frames that have been shifted with respect to each other during acquisition. The FLIR system is mounted on a moving platform, such as



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an aircraft, and the vibrations associated with the platform are used to generate the shifts. In this paper [2], the author describes some imaging systems employ detector arrays which are not sufficiently dense so as to meet the Nyquist criteria during image acquisition. This is particularly true for many staring infrared imagers. Thus, the full resolution afforded by the optics is not being realized in such a system. This paper presents a technique for estimating a high resolution image, with reduced aliasing, from a sequence of under sampled rotated and translationally shifted frames.

In this paper [3], the author describes Printing from an NTSC source and conversion of NTSC source material to high-definition television (HDTV) format are some of the recent applications that motivate super resolution (SR) image and video reconstruction from lower resolution (LR) and possibly blurred sources. Existing methods for SR image reconstruction are limited by the assumptions that the input LR images are sampled progressively, and that the aperture time of the camera is zero, thus ignoring the motion blur occurring during the aperture time. Because of the observed adverse effects of these assumptions for many common video sources, this paper proposes i) a complete model of video acquisition with an arbitrary input sampling lattice and a nonzero aperture time, and ii) an algorithm based on this model using the theory of projections onto convex sets to reconstruct SR still images or video from an LR time sequence of images. Experimental results with real video are provided, which clearly demonstrate that a significant increase in the image resolution can be achieved by taking the motion blurring into account especially when there exists large inter-frame motion.

In this paper [4], the author describes The three main tools in the single image restoration theory are the maximum likelihood (ML) estimator, the maximum a posteriori probability (MAP) estimator, and the set theoretic approach using projection onto convex sets (POCS). This paper utilizes the above known tools to propose a unified methodology toward the more complicated problem of super resolution restoration. In the super resolution restoration problem, an improved resolution image is restored from several geometrically warped, blurred, noisy and down sampled measured images. In this paper [5] the author describes the human visual system appears to be capable of temporally integrating information in a video sequence in such a way that the perceived spatial resolution of a sequence appears much higher than the spatial resolution of an individual frame. While the mechanisms in the human visual system which do this are unknown, the effect is no too surprising given that temporally adjacent frames in a video sequence contain slightly different, but unique, information. This paper addresses how to utilize both the spatial and temporal information present in a short image sequence to create a single high-resolution video frame. A novel observation model based on motion compensated sub-sampling is proposed for a video sequence. Since the re-construction problem is ill-posed, Bayesian restoration with a discontinuity-preserving prior image model is used to extract a high-resolution video still given a short low-resolution sequence.

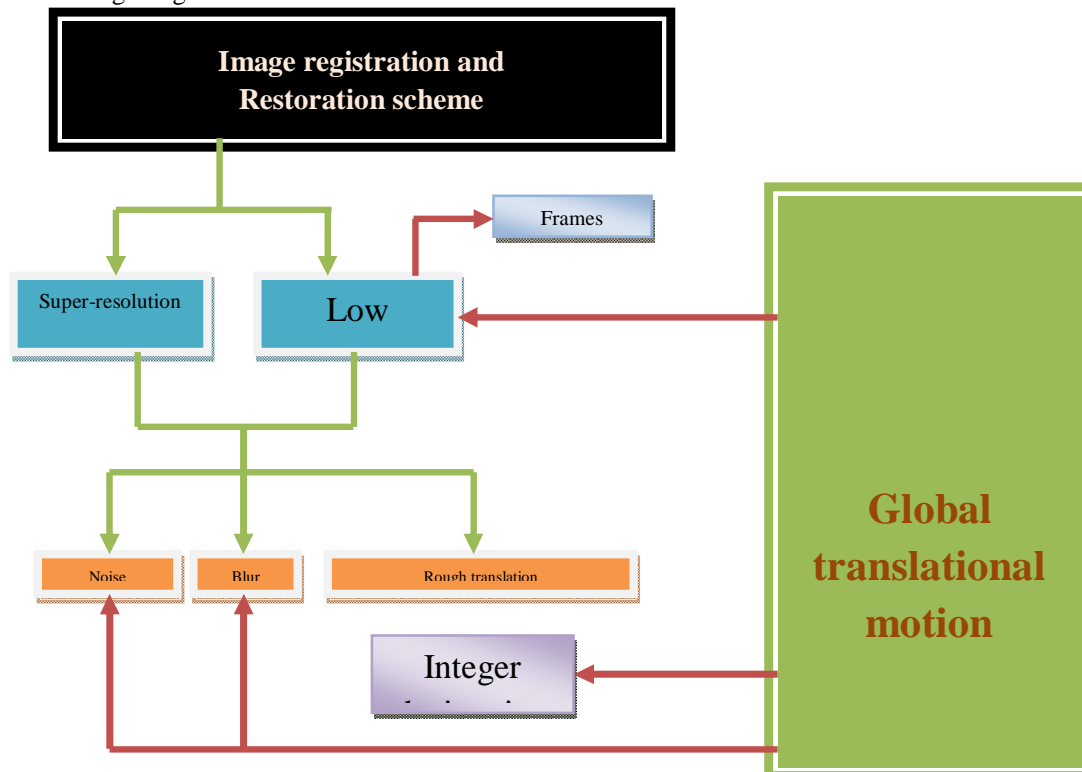
In this paper [6], the author describes In many imaging systems, the detector array is not sufficiently dense to adequately sample the scene with the desired field of view. This is particularly true for many infrared focal plane arrays. Thus, the resulting images may be severely aliased. This paper examines a technique for estimating a high resolution image, with reduced aliasing, from a sequence of undersampled frames. Several approaches to this problem have been investigated previously. In this paper [7], the author describes In this paper, we propose a technique for the estimation of the regularization parameter for image resolution enhancement (super-resolution) based on the assumptions that it should be a function of the regularized noise power of the data and that its choice should yield a convex functional whose minimization would give the desired high-resolution image. The regularization parameter acts adaptively to determine the tradeoff between fidelity to the received data and prior information about the image. In many imaging systems, the resolution of the detector array of the camera is not sufficiently high for a particular application. In this paper [8], the author describes In this correspondence, a constrained least-squares multichannel image restoration approach is proposed, in which no prior knowledge of the noise variance at each channel or the degree of smoothness of the original image is required. The regularization functional for each channel is determined by incorporating both within-channel and cross-channel information. It is shown that the proposed smoothing functional has a global minimizer. Considerable attention has been focused recently on image restoration techniques that are based on a multichannel formulation, since improved results can be obtained by incorporating cross-channel information into the restoration process.

In this paper [9], the author describes Super resolution reconstruction produces a high-resolution image from a set of low-resolution images. Previous iterative methods for super resolution had not adequately addressed the computational and numerical issues for this ill-conditioned and typically underdetermined large scale problem. We propose efficient block circulant preconditioners for solving the Tikhonov-regularized super resolution problem by the conjugate gradient method. In this paper [10], the author describes the super-resolution reconstruction problem is an inverse problem, dealing with the recovery of a single high-resolution image from a set of low quality images. In its general form, the super resolution problem may consist of images with arbitrary geometric warp, space variant blur and colored noise. Several algorithms were already proposed for the solution of this general problem. In this paper we concentrate on a special case of the super resolution problem, where the warp is composed of pure translation, the blur is space invariant and constant for all the measured images, and the additive noise is a white Gaussian noise. We exploit our previous results, and develop a new highly efficient super-resolution reconstruction algorithm for this case. This algorithm separates the treatment of the blur from the fusion of the measurements, and the resulting overall algorithm is non-iterative.

III. ARCHITECTURE DIAGRAM OF JOINT IMAGE REGISTRATION AND RESTORATION SCHEME FOR SUPER AND LOW RESOLUTION IMAGES

The phases involved in the proposed scheme are:

- Single and Multi-image blur deconvolution of low-resolution (LR) images
- Bayesian and Maximum a Posteriori Formulates
- Joint Image Registration and Restoration





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Single and Multi-image blur deconvolution of low-resolution (LR) images

The Coarse-to-fine scheme performs initial estimates of image and blurs kernels in lower scales using down sampled versions of observed LR images. After a few AM iterations at each scale estimation results are up sampled using bilinear interpolation used as inputs of next level. The Scheme increases processing speed and avoid local minima. The kernel size at coarsest level is 3×3 with up scaling factor. The apply constrains on pixel values of estimated HR image is fitted to expected range, i.e. 0 to 255. The PSFs are shifted to location of their centroid values less than zero are set to zero and then they are rescaled to sum up to on.

Bayesian and Maximum a Posteriori Formulates

This Approach for parameter estimation is maximum likelihood most probable parameters gave rise to the data are estimated. Direct assessment in closed form of likelihood function capturing statistical relation between unknown parameters and observations is complex because hidden variables. In super-resolution problem high-resolution image is appropriately contains hidden variable known and marginal likelihood is obtained from Bayesian integral derivatives. The Iterative algorithms are used to maximize either marginal likelihood or a lower bound guaranteed to converge to local maximum of marginal likelihood.

Once marginal likelihood and ML estimates of parameters are obtained posterior ith iteration to hidden variables is computed. If posterior is available mean is used as an estimate of hidden variables. Mean of hidden variables is calculated during E-step.

To Derive a Bayesian algorithm for super-resolution based on the E-M-algorithm in spatial domain. The use maximum-likelihood (ML) criterion to find the best estimate of the parameters of the image model. The Iterative approach called the Expectation-Maximization (E-M) algorithm employed to find the ML estimate of the model parameters to maximize expectation of complete data conditioned on incomplete data. To denote set of unknown parameters by probability density function (PDF) of the complete data.

In E-step of E-M algorithm conditional expectation of log is computed. In the M-step, this expectation is maximized. The Joint MAP estimation of the unknown parameters in high-resolution image. To derive MAP algorithm from Bayes' law posterior required for MAP estimate is calculated.

To compare Bayesian and MAP estimation methods on equal footing employ same imaging and prior model sused in our Bayesian method. To Estimate of high-resolution image with uncertain parameters and maximizing with respect to each unknown separately. The MAP algorithm requires the iterative computation maximizes joint probability by cyclic coordinate descent. The Minimization required was computed numerically using direction set methods.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section we evaluate performance of Joint Image Registration and Restoration Scheme for Super and Low Resolution Images through Mat lab. To confirm the analytical results, we implemented Bayesian formulation and MAP Technique in the image enhancement of Mat Lab and evaluated Bayesian and MAP the performance of technique.

The performance of is evaluated by the following metrics.

- Image accuracy
- Peak signal to noise ratio
- No of iteration

Table 1. Image accuracy

Image size	Image accuracy in Existing System	Image accuracy in Proposed System
45	70	87
50	81	97

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55	98	106
60	101	110
65	111	123

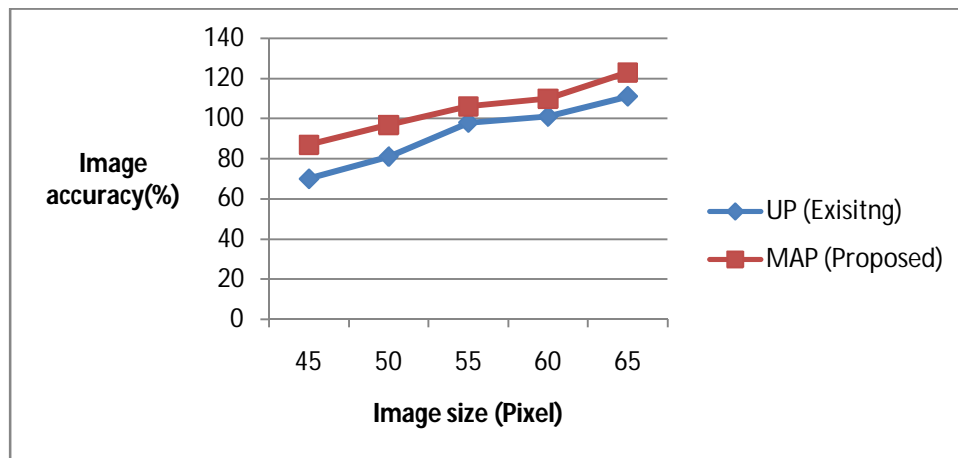


Fig 4.1. Image accuracy

Figure 4.1 demonstrates the image accuracy. X axis represents the image size in pixel whereas Y axis denotes the image accuracy using both the existing UP proposed MAP. When the image size increased, image accuracy gets increases accordingly. The rate of image accuracy is illustrated using the existing UP and proposed MAP. Figure 4.1 shows better performance of proposed MAP in terms of image size than existing and proposed MAP. Maximum a posteriori (MAP) formulation achieves 15 to 25% less image accuracy rate variation when compared with existing system

Table 2. Peak signal to noise ratio

Image size	Peak signal to noise ratio in Existing System	Peak signal to noise ratio in Proposed System
45	123	113
50	146	132
55	165	141
60	178	156
65	193	179

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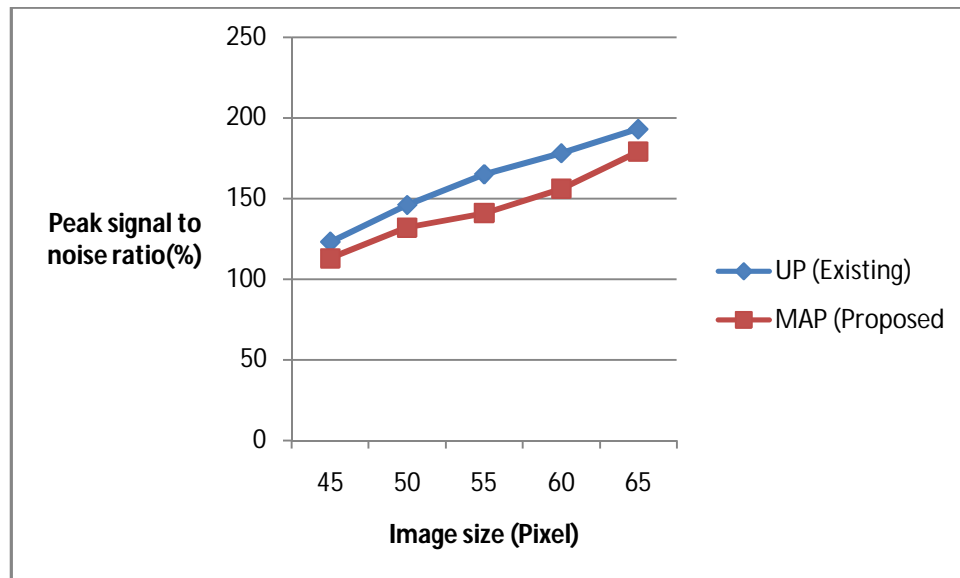


Fig 4.2. Peak Signal to Noise ratio

Figure 4.2 demonstrates the Peak Signal to noise ratio. X axis represents the Image size in pixel whereas Y axis denotes Peak signal to noise ratio the using both the UP and our proposed MAP. When the image size increased, peak signal to noise ratio also gets decreases accordingly. The Peak signal to noise ratio is illustrated using the existing UP and our proposed MAP. Figure 4.2 shows better performance of Proposed MAP in terms of images than existing UP and our proposed MAP. Maximum a posteriori (MAP) achieves 20 to 35% less Peak signal to noise ratio variation when compared with existing system.

Table 3. No of iteration

Image size	No of iteration in Existing System	No of iteration in Proposed System
45	23	17
50	21	14
55	19	11
60	17	7
65	15	4

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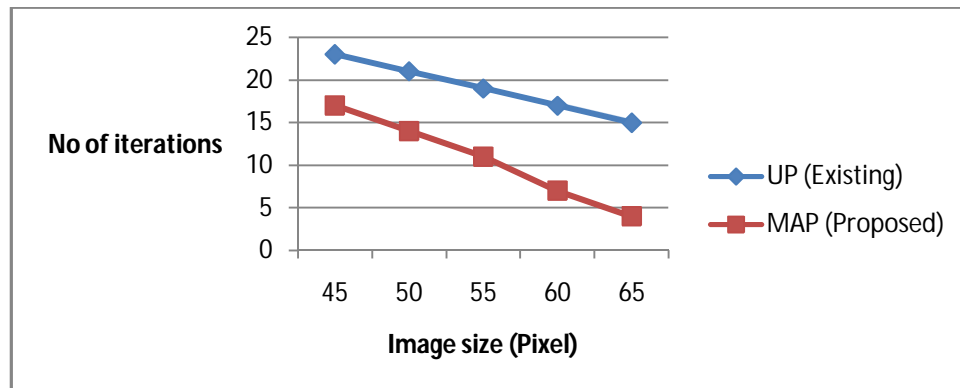
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Fig 4.3. No of iterations

Figure 4.3 demonstrates the No of iterations. X axis represents image size in pixel whereas Y axis denotes the No of iterations using both the UP and our proposed MAP Technique. When the image size increases the no of iterations also gets decreased. Figure 4.3 shows the effectiveness of No of iterations over different image size than existing UP and our proposed MAP. Maximum a posterior achieves 30% to 50% more No of iterations when compared with existing schemes

V. CONCLUSION

In this paper we performed an image deconvolution utilizing Maximum a posterior with Bayesian frames to answer user queries. Finally, we applied our analysis results to the design of a Maximum a posterior to identify and apply the best design parameter settings in Mat lab. we implemented the proposed scheme, and conducted comprehensive performance analysis and evaluation, which showed its efficiency and advantages over existing schemes.

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