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Super resolution image reconstruction using penalized-spline and phase congruency☆

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ABSTRACT

Super resolution reconstruction (SRR) of image is an ill-posed inverse problem. Several regularization based SRR (RSRR) methods have been suggested in the literature to obtain a unique and stable solution. In this paper, we propose a new RSRR framework by imposing two regularization constraints such as structural regularization term (SRT) and high frequency energy term (HFET). SRT utilizes the local phase coherence of the image to maintain consistency of structural features in the reconstruction process. HFET enables to preserve the complete set of high frequency components using phase congruency based on 2D Hilbert transform. Gradient descent method optimizes the regularized cost function. The optimization process starts with an improved initial high resolution (HR) image obtained by Penalized-spline interpolation. The iterative process progresses with an adaptive learning rate to yield a high quality HR solution at a faster rate of convergence. Simulation results validate the effectiveness of the proposed regularization scheme.

1. Introduction

High resolution (HR) images contain more image details, offer better visual perception and are hence successfully applied in various imaging applications such as video surveillance, remote sensing, forensic imaging and medical imaging. The current imaging system generates images with limited resolution and needs to be enhanced for obtaining HR. The possible reasons for the limited resolution may be due to different physical constraints, insufficient amount of photo detectors, inferior spatial sampling rate and inappropriate image capturing process. In recent decades, super resolution reconstruction (SRR) of image has been a low cost and efficient software level solution to enhance the resolution of the captured low resolution (LR) images. SRR of image employs various digital image processing methodologies and successfully satisfies the increasing demands for HR images at the consumer end.

SRR of image is the process of enhancing the resolution of the image reconstructed from a sequence of observed LR images. Fusion of critical information in the LR images is performed to reconstruct the HR image. LR images pass through three different steps viz. registration, interpolation and restoration to produce the HR image. However, inaccurate sub-pixel registration between LR images, ill-conditioned nature of degradation matrix and insufficient number of LR images model the SRR problem as ill-posed in nature [1]. The ill-posedness nature of the SRR problem provides non-unique, unstable so-

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lution and needs to be well regularized. In literature, many significant RSRR (regularization based SRR) methods [2–11] have been proposed by integrating the prior information about the HR image to solve the ill-posed problems.

Tikhonov regularization [2] is one of the popular reconstruction method which utilizes Lapalacian operator as the regularization constraint. This operator performs global minimization of high frequency components (HFCs). Consequently, noise along with some image details such as edges also get suppressed in the resultant image. Total variation (TV) based regularization method is used in [3] which utilizes the L_1 norm of the magnitude of the gradient to penalize the spatial variation of the image. However, due to consideration of piecewise constant image structures in the reconstruction process, steep local gradients in the image cannot be penalized properly. As an improvement to TV based regularization method, many methods [4,5] are proposed in the literature. A robust and computationally cheap regularization method termed as bilateral total variation (BTV) is implemented in [4] by measuring the L_1 norm of bilateral filter with TV regularization. This approach preserves more image details and removes outliers efficiently. But, the method is not locally adaptive. A spatially weighted TV (SWTV) regularization criterion is proposed in [5]. The weight parameter is measured via the difference curvature information of the image pixels. This method outperforms the method in [3], still the ringing artifacts exist near strong edges of the resultant image. Phase adaptive SRR of mammography images is performed in [6] via a third order Markov prior using complex wavelets (PACW). This method preserves the structurally significant features but provides poor results in non-homogeneous regions of image. Moreover, the quality of this reconstruction process degrades for MR and PET types of images. The above discussed RSRR methods are not locally adaptive and necessitate methods which will maintain a simultaneous balance between suppression of noise against preservation of image details. As a solution, new methods are proposed in the literature [7,8]. In [7], a novel regularization method termed as locally adaptive BTV (LABTV) is proposed. This method integrates fuzzy entropy to adaptively penalize different regions of the image. Though the method is locally adaptive, but periodic noise with ringing artifacts still present in the reconstructed images. Again, in this method, the regularization parameter (RP) is selected manually which is too hard to achieve. Another locally adaptive reconstruction method is proposed in [8]. This approach utilizes a multi-scale morphologic gain controlled regularization (GCBTV) method to enhance the edges and to reduce the noise at different scales. This method is also limited by the manual selection of RP as well as optimal size and shape of the structuring element. Moreover, ringing artifacts still prevail for images rich in geometrical shapes. In order to deal with the problem associated with the manual selection of RP, various methods [9–11] are proposed in the literature. In [9], phase-driven spatially variant regularization approach (PDSV) is proposed. In this approach, a spatially invariant RP based on the local phase coherence (LPC) measure of the image is used to regularize the TV and BTV constraint. The resultant images provide sharper edge details at the cost of more computational time. In [10], the method performs both deblurring and reconstruction by using an adaptive selection of sparse domain and regularization(ASDS). In this method, the prior model based on sparse representation of image patches, non-local self-similarity and adaptive selection of regularization as well as sparse parameter well preserves the reconstruction quality. However, the computational burden of the method is very prominent due to implementation of training data set for the learning process. In [11], locally adaptive RP is selected using particle swarm optimization (PSO) algorithm. The RP adaptively takes care of in-focus and out-focus region of image. The method is termed as local adaptive regularized super resolution (LARSR) method. The main difficulty in this method arises due to the premature convergence of PSO to local minima trapping.

The present work also proposes a RSRR framework by incorporating two regularization constraints, i.e., structural regularization term (SRT) and high frequency energy term (HFET). These regularization constraints help to preserve fine image details and to prune the effect of artifacts. The specialty of the proposed method lies in SRT maintaining consistency of the structural features and HFET enabling to preserve the complete set of HFCs irrespective of varying illumination or contrast. Gradient descent optimization method is adopted for the minimization of the cost function. The optimization process starts with an initial guess of the HR image and progresses with an adaptive learning rate to refine the initial estimate iteratively. Instead of using conventional interpolation methods, Penalized-spline (P-spline) interpolation is utilized to estimate the initial HR image. B-spline interpolation process is natively smooth in nature. Hence, P-spline interpolation scheme is used that enforces an extra regularization term to ensure efficient smoothness. As a result, it produces a sharper initial guess. Instead of a fixed value of learning rate, an adaptive learning rate based on the image characteristic is proposed for obtaining an improved quality of solution at a faster convergence rate.

The remaining of the paper is arranged as follows. The imaging model, the problem statement and a concise idea about the SRR via regularization process are discussed in Section 2. Section 3 presents the proposed regularization framework along with the P-spline interpolation scheme for the estimation of initial HR image. The comparative result analysis and quality assessment of the proposed work with other existing significant state of art methods are discussed in Section 4. Conclusion along with the future scope of the work is described in Section 5.

2. Imaging model

The imaging model plays an important role in the image SRR process. It provides the idea to understand the resolution limiting factors for the captured images. The image observation model used in the present work is depicted in Fig. 1. The mathematical formulation for the generation of the k^{th} LR image from the HR image X is given in Eq. (1).

$$l_k = Do_k H_k F_k X + \eta_k \quad k = 1, 2, \ldots\ldots\ldots K \tag{1}$$

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