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Preserving quality in minimum frame selection within multi-frame super-resolution

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ABSTRACT

As there are data redundancies in successive frames in a multi-frame super resolution (SR) algorithm, one can expect that discarding some of these superfluous frames would have no impact on the quality of the high resolution (HR) output image. The present paper presents an efficient algorithm for selecting the proper combination of the minimum frames required for multi-frame SR algorithms so as to not only preserve the quality of the obtained HR output, but also reduce the SR procedure complexity and memory. To achieve this, the present study first seeks to prove that minimizing the spectral interference between the selected frames for SR procedure will result in maximizing the HR output power. Then, the criterion for measuring the Upper Bound on Spectral Interferences (UBSI) among the selected frames for SR procedure is presented; the formulation is expressed in such a way that it can be extended to global sub-pixel translations between frames. Our proposed frame selection algorithm evaluates all candidate combinations from input frames so that the best option capable of minimizing the UBSI can be selected. In order to evaluate our proposed frame selection algorithm, five well-known SR image reconstruction methods are applied both in four standard simulated images and in three well known real video sequences, employing two different procedures: Using our proposed frame selection algorithm and otherwise. The obtained results indicate that when our proposed frame selection algorithm is applied, the quality of the HR output images is preserved tantamount to considering all available frames. Besides, the computational complexity of the SR algorithms is dramatically reduced adopting the proposed frame selection algorithm, for the number of frames engaged in the SR is diminished. Also compared with the SR algorithms presented in the literature, our proposed frame selection method takes relatively negligible time to execute.

1. Introduction

High resolution images are of critical importance in such numerous areas of image processing applications as enhancing daily life (regular) videos, surveillance monitoring, earth observation, remote sensing, medical diagnosis, target detection, and astronomical observations [1]. Unfortunately, on account of physical constraints, technological limitations, and different parasitic noises, the final output images of the detector arrays do not have the desirable resolution and quality. Therefore, the multi-frame super-resolution (SR) technique is utilized to reconstruct a high resolution (HR) image from a low-resolution (LR) noisy frame stream.

The concept of the multi-frame SR reconstruction technique was first introduced in 1984 by Tsai and Huang in the frequency domain [2]. Their method was subsequently improved by other researchers. To take an example, Kim et al. extended Tsai and Huang's method by adding spatial blurring and observation noise [3]. Discrete cosine transforms (DCT) and discrete wavelet transform (DWT) based methods were respectively proposed in [4] and [5,6]. Later, many spatial domain approaches were introduced to overcome the difficulties and defects/limitations of the frequency domain SR reconstruction methods. Stark and Oskoui proposed the projection onto convex set (POCS) foundation for SR restoration for the first time [7]. The POCS-based approaches drawing upon prior information/data in reconstruction processes are lacking in several respects: No unique solution, slow convergence, and especially high computational costs.

Recently, the regularized methods are among those favored by researchers considered from the viewpoint of effectiveness and flexibility. Accordingly, some recent articles on SR have focused on regularized frameworks [1].

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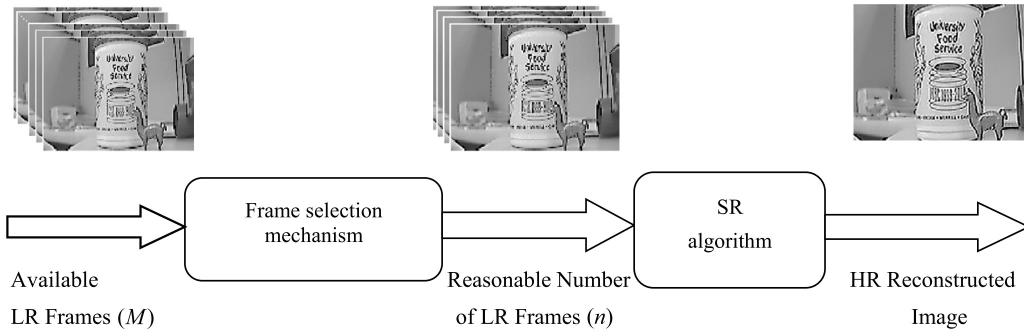

Fig. 1. Multi-frame SR procedure including frame selection mechanism and SR algorithm.

To take some examples, Yuan et al. proposed a spatially weighted total variation (TV) SR algorithm where they used curvature to identify variation area of each pixel [8]. Also, they determined regularization parameter by different curvatures to control the TV weights. In their next research study, they developed a regional total variation (TV) model spatially adaptive drawing upon k-means clustering based on local spatial information to control the regularization strength in each classified region [9].

Yue et al. employed combination of L1 and L2 norms to adaptively assign local norm values for different pixel locations in accordance with impulse noises [10].

Shen et al. introduced a method to adaptively determine the optimal norms for the two terms of fidelity and regularization in both the image restoration and SR reconstruction [11]. Recently, Köhler et al. have developed a robust multi-frame super-resolution method by introducing a weighted Gaussian observation model applying weighted bilateral total variation as the regularization term [12]. To resolve SR problem, they have offered an iteratively re-weighted minimization algorithm based on majorization–minimization optimization.

High computational complexity is one of the common challenges and practical limitations in the majority of the SR reconstruction algorithms cases, especially when all available frames are fed into the SR algorithm. Some efforts have been made to overcome this problem. For example, block-based method [13] and well suited parallel reconstruction mechanism, including fast map-based super-resolution [14] have been proposed to speed up the SR procedure.

Alternatively, one can select a limited number of frames equaling that of the minimum frames required to constitute a determined system or more than the minimum number can selected, in which case, an over-determined system is formed. Unfortunately, an inconvenient set of frames results in a strongly degraded HR images pointing to the importance of frame selection mechanism.

Furthermore, the successive frames are so highly correlated that eliminating redundant data would have no impact on the HR image quality. That is to say, while the extra data does not improve the quality of the resultant HR image, it would augment the computational complexity to a considerable degree. In order to make the SR algorithm feasible in real-time operation, a few LR images must be selected out of an available sequence of the same scene being different in sub-pixel displacement.

Fig. 1 shows an ordinary multi-frame SR procedure comprising two main parts: Frame selection mechanism and SR algorithm. If there are M available frames in the sequence, the frame selection mechanism selects n frames based on relation (1):

$$N \le n \le M \tag{1}$$

where $N = (\mathrm{srf})^2$ is the minimum frames required being sufficient in some conditions [15] and which can constitute a determined system-srf being the SR factor or the magnification factor.

So far, quite a number of the SR algorithms have been offered to reconstruct high quality HR image. Not just that, the frame selection mechanism also plays a crucial role in HR image output quality. If the data content in the selected frames is not sufficient for the SR algorithm, the reconstructed HR image becomes strongly degraded. Additionally, if the selected frames are captured without appropriate transformations (e.g. sub-pixel translations), the SR procedure fails to restore the details of the HR image. The worst case happens when the acquired frames contain no displacement [15].

Thus, the present paper aims at proposing a novel frame selection method capable of being utilized in conjunction with any multi-frame SR algorithm and selecting minimum frames from all available LR frames for achieving both higher HR reconstructed image quality and lower SR computational cost.

In section 2 that comes next, initially we have furnished a mathematical explanation of the problem to be addressed and then the required formulation for introducing our newly proposed criterion i.e., the upper bound of spectral interference (UBSI) is offered. Section 3 presents and evaluates the proposed frame selection algorithm based on minimizing UBSI where different cases are taken into account. In the final section, experimental results verify the effectiveness of the algorithm proposed – while having different reconstruction methods in view both simulated and real frames.

2. The proposed criterion

This section introduces our proposed criterion related to the upper bound on the spectral interference (UBSI) from among the desired frames. This is the criterion being applied in our proposed frame selection algorithm.

Assume N low resolution (LR) frames where $N = (\mathrm{srf})^2$, $\mathbf{x}$ is the desired HR image, and $\mathbf{y}_r$ is the rth LR frame, all of which are column vectors in the alphabetical order representing gray values of their pixels. The conventional model for the observation of $\mathbf{y}_r$ is [16]:

$$\mathbf{y}_r = \mathbf{DHF}_r\mathbf{x} + \mathbf{w}_r, \quad r = 1, 2, \ldots, N, \tag{2}$$

where $\mathbf{H}$, $\mathbf{F}_r$ and $\mathbf{D}$ denote matrix forms of the point spread function (PSF) of the image acquisition system, the geometric transformation of the rth HR image from the desired HR image $\mathbf{x}$, and the down-sampling matrix, in the order mentioned. Also, $\mathbf{w}_r$ denotes measurement noise which is generally assumed white zero mean Gaussian noise being uncorrelated among different frames. If all observation relations are incorporated, the whole model can be written as:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_N \end{bmatrix} = \begin{bmatrix} \mathbf{DHF}_1 \\ \vdots \\ \mathbf{DHF}_N \end{bmatrix} \mathbf{x} + \mathbf{W} \tag{3}$$

where $\mathbf{W}$ is $[\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_N]'$ and where $'$ denotes transposes.