Recent Developments in Superresolution

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Abstract—**Super resolution imaging refers to inferring the missing high resolution image from low resolution image(s). Super resolution methods are generally classified into reconstruction based and learning based methods. This paper focuses on recent developments in Image Superresolution in both reconstruction based and learning based methods and also discusses about the research in Superresolution algorithm evaluation using image quality measures.**

Keywords-Reconstruction based Super-Resolution; Learning based Super-Resolution; Super-Resolution.

I. INTRODUCTION

Super-resolution image restoration refers to the image processing algorithm which produces high quality, superresolution (SR) images from a set of low-quality, low resolution (LR) images. It is generally regarded as consisting of three steps – image registration, fusion, and deblurring [1].

While most methods have been proposed by researchers for super-resolution based on multiple low-resolution images of the same scene, some of the research work has been on generating a high-resolution image from a single low resolution image, with the help of a set of one or more training images from scenes of the same or different types. These are named as reconstruction based and learning based methods respectively. Learning based methods use neural network for estimating HR image and are also referred as the single-image superresolution problem.

II. SUPER-RESOLUTION METHODS

A. Learning-based Super-resolution

Learning-based super-resolution algorithms can roughly be characterized as nearest neighbor (NN)-based estimation: During the training phase, pairs of low-resolution and corresponding high-resolution image patches (subwindows of images) are collected. Then, in the super-resolution phase, each patch of the given low-resolution image is compared to the stored low-resolution patches, and the high-resolution patch corresponding to the nearest low-resolution patch and satisfying a certain spatial neighborhood compatibility is selected as the output. For instance, Freeman et al. [2] posed the image super-resolution as the problem of estimating high-frequency details by interpolating the input low-resolution image into the desired scale (which results in a blurred image). Then, the super-resolution is performed by the NN-based estimation of high-frequency patches based on the corresponding patches of input low-frequency image and resolving the compatibility of output patches using a Markov network.

B. Reconstruction-based Super-resolution

The basic principle for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured from the same scene. In SR, typically, the low resolution images represent different “looks” at the same scene. That is, LR images are subsampled (aliased) as well as shifted with subpixel precision. If the LR images are shifted by integer units, then each image contains the same information, and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different subpixel shifts from each other and if aliasing is present, however, then each image cannot be obtained from the others. In this case, the new information contained in each LR image can be exploited to obtain an HR image. To obtain different looks at the same scene, some relative scene motions must exist from frame to frame via multiple scenes or video sequences. Multiple scenes can be obtained from one camera with several captures or from multiple cameras located in different positions.

III. MATHEMATICAL MODEL FOR RECONSTRUCTION-BASED SUPER-RESOLUTION

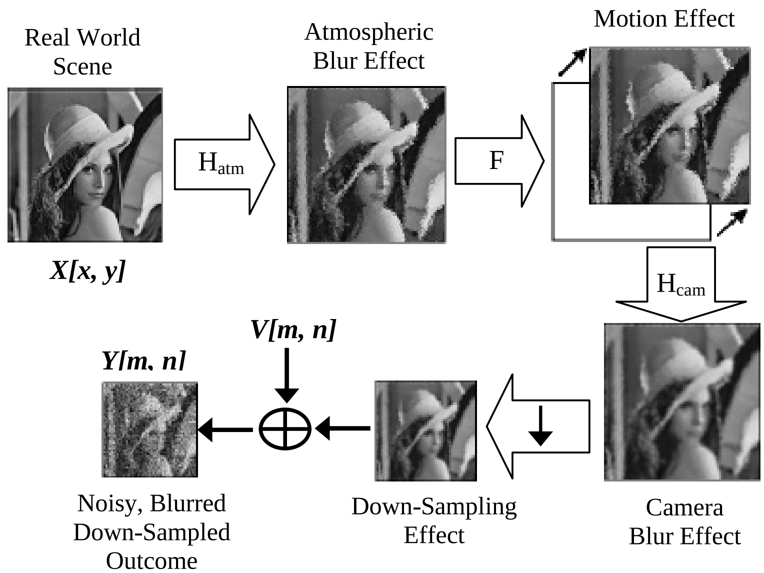

Figure 1. Block diagram representation of (1), where X(x,y) is the continuous intensity distribution of the scene, V [m, n] is the additive noise, and Y [m, n] is the resulting discrete low-quality image.

The first step to comprehensively analyze the SR image reconstruction problem is to formulate an observation model that relates the original HR image to the observed LR images. A dynamic scene with continuous intensity distribution $\underline{X}$ is seen to be warped at the camera lens because of the relative motion between the scene and camera. The images are blurred both by atmospheric turbulence and camera lens by continuous point spread functions $H_k = H_k^{atm} H_k^{cam}$. Then, they will be discretized at the CCD resulting in a digitized noisy frame $\underline{Y}$. We represent this forward model by the following [3]:

$$\underline{Y}_k = D_k H_k F_k \underline{X} + V_k \qquad k = 1,2, \ldots, N \tag{1}$$

where F_k is the geometric warp operator between the high-resolution frame X and k^{th} low-resolution frame Y_k which are rearranged in lexicographic order (X and Y_k present their matrix form). The camera's point spread function (PSF), is modeled by the blur matrix H_k, and D_k represents the decimation operator. V_k is the additive noise and N is the number of available low-resolution frames. Fig. 1 illustrates this equation.

IV. RECENT DEVELOPMENTS

Here we focus on the recent development in both the methods vis-à-vis Learning-based and Reconstruction-based Super-resolution.

A. Learning-based Super-resolution

Kernel ridge regression (KRR) is adopted in [6] to learn a map from input low-resolution images to target high-resolution images based on example pairs of input and output images. To reduce the time complexity of training and testing for KRR, a sparse solution is found by combining the ideas of kernel matching pursuit and gradient descent. As a regularized solution, KRR leads to a better generalization than simply storing the examples as has been done in existing example-based algorithms and results in much less noisy images. In comparison with the non-example-based methods, the proposed method resulted in a better preservation of texture details and more natural transitions of pixel values across strong edges.

Texture mapping is a method for adding surface texture/color to a 3D mesh model, and enhances the reality of the 3D mesh model. As compared to using computer generated textures, real images taken from multiple viewpoints as textures produce more realistic images. An artifact-free superresolution texture mapping from multiple-view images is presented in [7] by Masaaki Iiyama et al. The multiple-view images are upscaled with a learning-based superresolution technique and are mapped onto a 3D mesh model. However, mapping multiple-view images onto a 3D model is not an easy task, because artifacts may appear when different upscaled images are mapped onto neighboring meshes. Cost function is defined that becomes large when artifacts appear on neighboring meshes, and the method seeks the image-and mesh assignment that minimizes the cost function.

A learning-based method for super resolution is proposed by YanJie Ma et al [10]. Super-Resolution image reconstruction based on K-means-Markov network belongs to the method based on learning. Authors make use of Markov network to learn the details of the HR image corresponding to different regions of the LR images in the training set, and then use the relationship learned to predict the information of the input LR image. Firstly, they set up a training sample set, containing LR image patches and the corresponding HR patches. And then, put this patches into Markov network as nodes of it, learn the parameters of the network from training samples, take advantage of Bayesian belief propagation mechanism to find out the most probable candidate of the HR estimate for the input image, as a result, to obtain super-resolution image.

B. Reconstruction-based Super-resolution

In [4] Kai Xei proposes an efficient approximate method based on the incomplete orthogonalization Arnoldi Process. The method uses a few previous orthogonal vectors for Arnoldi process. The others are not needed in the process and may be discarded. Hessenberg matrix obtained from the incomplete orthogonalization process has a band structure different from the previous similar upper triangular matrix. The computational complexity of the L-curvature may be dropped. Arnoldi process spends too much to yield more Arnoldi vectors. Incomplete Orthogonalization Method (IOM) can truncate Armoldi process so that we may keep a few Arnoldi vectors for each step of Arnodi process. Thus the technique greatly reduces computational cost so as to computes efficiently for the L-curvature in super-resolution restoration.

Andrew Gilman et. al. in [5] presented a novel technique for resampling a non-uniformly sampled image onto a uniform grid that can be used for fusion of translated input images. The proposed method can be very fast, as it can be implemented as a finite impulse response filter of low order (10th order results in good performance). The technique is based on optimising the resampling filter coefficients using a simple image model in a least squares fashion. The method is tested experimentally on a range of images and shown to have similar results to that of a least-squares optimal filter. Experimental results show that the resampling filters optimised on the proposed image model perform similarly to the least-squares optimal filters. The model-based filters also outperform a number of commonly used methods for non-uniform image interpolation used in image super-resolution.

The proposed method in [8] applies random shifts to reference high-resolution images, and the obtained images were downsampled. Then the high-resolution images were reconstructed from these low-resolution images by the super-resolution algorithm and compared with the reference images. To test the stability of the proposed method to the motion vectors errors, a noise was added to the motion vectors. A random uniformly distributed value in [-1; 1] range was added to every motion vector for a quarter of the input images. A random value in [-0:25; 0:25] range was added to motion vectors for other images. The results for the proposed super-resolution method has better visual quality than of the method based on median averaging and the method based on Gaussian averaging. Median averaging produces noisy edges while Gaussian averaging blurs the edges in the case of errors in motion vectors estimation. The metrics BEP (Basic Edges Points) calculates the mean square error (MSE) in the points of sharp and isolated edges — basic edges. The metrics BEN (Basic Edges Neighborhood) calculates the MSE in the basic edges neighborhood. The weighted median averaging shows better BEN and BEP than the Gaussian averaging, but the results are contradictory in comparison to the median averaging. The weighted median averaging gives better results than the median averaging in edge areas (BEP areas), but is worse in the areas near the edges (BEN areas). Nevertheless the problem of edge reconstruction is usually more significant than the reconstruction of non-edge areas in the case of erroneous motion vectors. Thus we make a conclusion that the weighted median averaging method shows better results than the median averaging method or the Gaussian averaging method.

A new method for multi-frame superresolution reconstruction is proposed by Quan Xiao [11]. It builds up with three steps: motion estimation, frame interpolation and fusion, deblurring. Based on the pure translations motion model, a simple motion estimation method is firstly proposed. All measured frames are subsequently located to a fixed grid and interpolated using an effective technique called Steering Kernel Regression. Then, the reconstruction frame is obtained by fusion high-resolution pixels selected from all of the interpolated frames. Finally, the reconstructed frame is deblurred at the last step. Experimental results on simulated and real data confirm the effectiveness of the proposed method and demonstrate the Steering Kernel Regression's superiority to other interpolate methods such as cubic interpolation. The method is based on tracking a group of feature points which can attain sub-pixel accuracy. After located all frames, a novel interpolation method called Steering Kernel Regression is adopted to interpolate the low resolution frame. The steering kernel is a locally adapted kernel which takes into account both the local density of the available samples and the actual values of available samples. Hence, it can be effective in preserving image details.

C. Evalution of Super-Resolution Algorithms

The goal of super-resolution (SR) techniques is to enhance the resolution of low-resolution (LR) images. How to evaluate the performance of an SR algorithm seems to be forgotten when researchers keep producing algorithms. Li TIAN et al [9] presented a task-oriented method for evaluating SR techniques. The method includes both objective and subjective measures and is designed from the viewpoint of how SR impacts many essential image processing and vision tasks. The authors have evaluated some state-of-the-art SR algorithms and the results suggest that different SR algorithms should be utilized for different applications. In general, they reflect the consistency and conflict between objective and subjective measures as well as computer vision systems and human vision systems do. The authors have proposed a task-oriented evaluation method for SR techniques in this study. It consists of five objective and subjective measures. 1) Modified Peak Signal-to-Noise Ratio (MPSNR), 2) Point Reproduction Ratio (PRR) and 3) Mean Segment Reproduction Ratio (MSRR), which involve intensity, interest point detection and image segmentation, respectively, are designed as objective measures. Image quality is also evaluated by human observers answering different questions, then quantified scores including 4) Mean Opinion Scores (MOS) and 5) Variance Opinion Scores (VOS) are calculated as subjective measures.

Vishal R. Jaiswal et. al. [12] have compared two multiframe image super-resolution algorithms namely Robustand Fast Robust algorithms. Variety of image quality measures are used to assess the results. Results show that Robust algorithm gives slightly better results as compared to Fast Robust but consumes more time.

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