A Survey On Single Image Superresolution

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Abstract: The key objective of super-resolution (SR) imaging is to reconstruct a higher-resolution image based on a set of images, acquired from the same scene and denoted as 'low-resolution' images, to overcome the limitation and/or ill-posed conditions of the image acquisition process for facilitating better content visualization and scene recognition. In this paper, we provide a comprehensive review of SR image methods. The SR image approaches reconstruct a single higher-resolution image from a set of given lower-resolution images For the reconstruction stage a SR reconstruction model composed of the L1 normdata fidelity and total variation (TV) regularization is defined, with its reconstruction object function being efficiently solved by the steepest descent method. Other SR methods can be easily incorporated in the proposed framework as well. Specifically, the SR computations for multi-view images computation in the temporal domain are discussed.

Keywords Super-resolution imaging, Resolution enhancement , Regularization

I. INTRODUCTION

Image superresolution refers to image processing algorithms that produce high quality, high resolution (HR) images from a set of low quality, low resolution (LR) images or from a single image. Naturally there is always demand of a better quality image. The level of image detail is crucial for the performance of several computer vision algorithms. Target recognition, detection and identification systems are some of the military applications that require the highest quality achievable. License plate readers, surveillance monitors, and medical imaging applications are some examples of the civilian applications with the same requirement. In many visual applications, both civilian and military, the imaging sensors have poor resolution outputs. When resolution cannot be improved by replacing sensors, either because of cost or hardware physical limits, we can resort to superresolution algorithms. Even when superior equipment is available, superresolution algorithms are an inexpensive alternative.

Super resolution is the process of obtaining high resolution image from one or more low resolution images. When image captured by low resolution camera three main artifacts occur, namely aliasing, blurring and additive noise. An aliasing occurs due to the low sampling rate. This causes the loss of high frequency contents from the image. High frequency having information about edges and textures, so there are ultimate artifacts occurs at the edges in the image. A blurring occurs due to the relative motion between image and camera. An atmospheric noises like rainy atmosphere and dusty atmosphere cause additive noise in image. So, one can say that the super resolution is the process of recovering the missing high frequency details and removing the degradation that arise during the image acquisition process. Multiframe image Super Resolution (SR) is the term used to refer to the image processing done to obtain a High Resolution (HR) image from multiple Low Resolution (LR) images. SR techniques are applied on multiple LR image captured from the same scene in order to increase spatial resolution for a new image of that same scene. That is, LR images are sub sampled (aliased) as well as shifted with sub pixel precision. If the LR images are shifted by integer units, then each image contains the same information, and then there is no new information that can be used to reconstruct a HR image. If the LR images have different sub pixel shifts from each other and if aliasing is present, 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 a 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. Frames also can be obtained of one scene but from a video sequence. This will be the chosen method used in this paper. If these scene motions are known or can be estimated within sub pixel accuracy and then, by combining these LR images, SR image reconstruction is possible.

II. OBSERVATION MODEL FOR SUPER-RESOLUTION IMAGE

As depicted in Fig. 1, the image acquisition process is mod- eled by the following four operations: (i) geometric trans- formation, (ii) blurring, (iii) down-sampling by a factor of q1 × q2, and (iv) adding with white Gaussian. Note that the geometric transformation includes translation, rotation, and scaling. Various blurs (such as motion blur and out-of-focus blur) are usually modeled by convolving the image with a low-pass filter, which is modeled by a point spread func- tion (PSF). The given image (say, with a size of M1 × M2)is considered as the high-resolution ground truth,which is to be compared with the high-resolution image reconstructed from a set of low-resolution images (say, with a size of L1 × L2 each; that is, L1 = M1/q1 and L2 = M2/q2) for conducting performance evaluation. To summarize mathematically,

y(k) = D(k)P(k)W(k)X + V(k), (1)

= H(k)X + V(k), (2)

where y(k) andXdenote the kth L1×L2 low-resolution image and the original M1×M2 high-resolution image, respectively, and k = 1, 2,...,ρ. Furthermore, both y(k) and X are repre- sented in the lexicographic-ordered vector form, with a sizeof L1L2 ×1 and M1M2 ×1, respectively, and each L1 × L2 image can be transformed (i.e., lexicographic ordered) into a L1 L2×1 column vector, obtained by ordering the image rowby row. D(k) is the decimation matrix with a size of L1 L2 ×

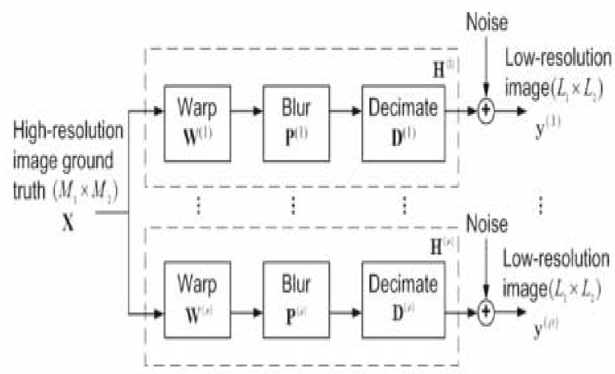

Fig. 1 The observation model,establishing the relationship between the original high-resolution image and the observed low-resolution images.The observed low-resolution images are the warped, blurred,down-sampled and no is version of the original high-resolution image .

M1M2, P(kis the blurring matrix of size M1M2 × M1M2, andW(k) is the warpingmatrix of size M1M2 ×M1M2. Con-sequently, three operations can be combined into one trans- form matrix H(k) = D(k)P(k)W(k) with a size of L1 L2 ×M1M2. Lastly, V(k) is a L1L2 × 1 vector, representing the white Gaussian noise encountered during the image acqui- sition process. Note that V(k) is assumed to be independent with X. Over a period of time, one can capture a set of (say,ρ) observations . With such establish-ment, the goal of the SR image reconstruction is to produce one high-resolution image X based. It is important to note that there is another observation model commonly used in the literature (e.g., [34–37]). The only difference is that the order of warping and blurring oper- ations is reversed; that is, y(k) = D(k)W(k)P(k)X + V(k). When the imaging blur is spatio-temporally invariant and only global translational motion is involved among multiple observed low-resolution images, the blur matrix P(k) and the motion matrix W(k) are commutable. Consequently, these two models coincide. However, when the imaging blur is spatio-temporally variant, it is more appropriate to use the second model. The determination of themathematicalmodel for formulating the SR computation should coincide with the imaging physics (i.e., the physical process to capture low-resolution images from the original high-resolution ones).

III. SUPER-RESOLUTION IMAGE RECONSTRUCTION

The generation of the low resolution image can be modeled as a combination of smoothing and down-sampling operation of natural scenes by low quality sensors. Super resolution is the inverse problem of this generation process. One criteria of solving this inverse problem is minimizing the reconstruction error. Various methods are proposed in literature to deal with the inverse problem. In following section I categorize the different SR methods available in existing paper.

A. Interpolation Methods

Image interpolation is the process of converting the image from one resolution to other resolution. This process is performed on a one dimension basis row by row and then column by column. Image interpolation estimates the intermediate pixel between the known pixels by using different interpolation kernel.

- **Nearest Neighbor Interpolation**

Nearest neighbor interpolation is the simplest interpolation from the computational point of view. In this, each output interpolated pixel assign the value of nearest sample point in the input image [2]. This process just displaces the intensity from reference to interpolated one so it does not change the histogram. It preserves the sharpness and dose not produce the blurring effect but produce aliasing.

- **Bi-linear Interpolation**

In Bi-linear interpolation the intensity at a point is determined from weighted some of intensity at four pixel closet to it. It changes the intensity so histogram is also change. It slightly smoothes the image but does not create an aliasing effect.

- **Bi-cubic Interpolation**

In cubic interpolation intensity at point is estimated from the intensity of 16 closest to it. The basis function is Bi-cubic gives smooth image but computationally demanding.

- **B-spline Interpolation**

Spline interpolation is the form of interpolation where interpolant is a special piecewise polynomial called a spline. There is a whole family of the basis function used in interpolation which is given as [2]. Higher order interpolation is much more used when image required many rotation and distortion in separate step. However for single step enhancement is increased processing time.

- **Hybrid Approach of Interpolation**

In 2008, H. Aftab et al. [3] proposed a new hybrid interpolation method in which the interpolation at edges is carried out using the covariance based method and interpolation at smooth area is done by using iterative curvature based method. After finding edges and smooth area using information from the neighborhood pixels edge is interpolated using covariance based method. The covariance coefficient of HR image is obtaining using co-variance parameter of LR image. In smooth are a curvature interpolation is carried out by first performing bilinear interpolation along the direction where the second derivative is lower and in diagonal case the difference between diagonal is calculated and use bilinear interpolation where the intensity difference is less. This method has significant advantage in terms of the processing time, peak signal to noise ratio and visual quality compared to bilinear, bi-cubic and nearest neighbor.

B. Iterative back projection algorithm

In this algorithm [1]-[3] back projection error is used to construct super resolution image. In this approach the HR image is estimated by back projecting the error between the simulated LR image and captured LR image. This process is repeated several times to minimize the cost function and each step estimate the HR image by back-projecting the error. The main advantage of this method is that this method converges rapidly, less complexity and low-less number of iteration is required. In recently numbers of improvements are used with this approach which is different edge preserving mechanisms.

C. Robust Learning-Based Super-Resolution

This algorithm [5] synthesizes a high-resolution image based on learning patch pairs of low- and high-resolution images. However, since a low-resolution patch is usually mapped to multiple high-resolution patches, unwanted artifacts or blurring can appear in super-resolved images. In this paper, we propose a novel approach to generate a high quality, high-resolution image without introducing noticeable artifacts. Introducing robust statistics to a learning-based super-resolution, we efficiently reject outliers which cause artifacts. Global and local constraints are also applied to produce a more reliable high- resolution image. Learning-based super-resolution algorithms are generally known to provide HR images of high quality. However, their practical problem is the one-to- multiple mapping of an LR patch to HR patches, which results in image quality degradation.

D. An Efficient Example-Based Approach for Image Super-Resolution

This algorithm [6], [7] uses learning method to construct super resolution image. The main contributions of these algorithms are: (1) a class-specific predictor is designed for each class in our example-based super-resolution algorithm – this can improve the performance in terms of visual quality and computational cost; and (2) different types of training set are investigated so that a more effective training set can be obtained. The classification is performed based on vector quantization (VQ), and then a simple and accurate predictor for each category, i.e. a class-specific predictor, can be trained easily using the example patch-pairs of that particular category. These class-specific predictors are used to estimate, and then to reconstruct, the high-frequency components of a HR image. Hence, having classified a LR patch into one of the categories, the high-frequency content can be predicted without searching a large set of LR-HR patch-pairs.

E. Learning Based Super Resolution using Directionlets

In this algorithm [9] example based method using directionlets (skewed anisotropic wavelet transform) are used to generate high resolution image. It does scaling and filtering along a selected pair of direction not necessary horizontal and vertical like wavelet transform. In this approach the training set is generated by subdividing HR images and LR images into the patches of size 8*8 and 4*4 respectably. And then best pair of the direction is assign to each pair from five set of directions [(0,90),(0,45),(0,-45),(90,-45),(90,45)] and then grouping the patches according to direction which reduce the searching time. Input LR image is contrast normalized and then subdivided into 4*4 patches. Each patch is decomposed into eight bands passing using directionlets. The directional coefficient of six bands HL,HH,VL,VH,DL,DH are learn from training set. Minimum absolute difference MAD criterion is used to select the directionlets coefficient. For AL and AH cubic interpolated LR image is used. These learned coefficients are used to obtain SR image by taking inverse directionlets transform. At the end contrast normalize is undo. Simple wavelet which is isotropic and does not follow the edges results in the artifacts which are removed in this case.

IV. RELATION TO OTHER METHODS

Since this survey paper proposes a new approach to the super resolution restoration problem, it is appropriate to relate this new approach to the methods already known in the literature. In the sequel, we will present a brief description of each of the existing methods in light of the new results. The three main known methods for super resolution restoration are the IBP method [31]–[33], the frequency domain approach [24]–[26], the POCS approach [34]–[35], and the MAP approach [37]. This section will concentrate on these four methods.

A. The IBP Method

The IBP method [31]–[33] is an iterative algorithm that projects the temporary result onto the measurements, simu- ating them this way. The above simulation error is used to update the temporary result. If we take this exact reasoning and apply it on our proposed model in (2.1), denoting the temporary result at the th step by , we get for the simulated measurements . The proposed update equation in the IBP method [31]–[33] is given in scalar form, but when put in matrix notations, we get where Q(k) are some error relaxation matrices to be chosen. The configuration obtained in (4.1) is a simple error relaxation algorithm (such as the steepest descent, the Gauss–Siedel algorithms, or other algorithms), which minimizes a quadratic error as defined in (2.4). This analogy means that the IBP method is none other than the ML (or least squares) method proposed here without regularization. In the IBP method presented in [31]–[33], the matrices Q(k) were chosen to be Q(k)={[1/f(k)]*[1/C(k)]*[D(k)]} where C(k) is a reblurring operator, and D(k) is an interpolation to be determined [31]–[33]. If we choose the simple SD algorithm for the solution of (2.5), we get that . This result implies that choosing the transpose of the blur matrix as the reblurring operator, and zero padding as the interpolation operator gives almost the same result as the IBP method. The only difference is the choice of the warp matrix in the above two configurations. Since , the IBP method uses the additional positive-definite inverse of the matrices to the error relaxation matrices proposed by the SD algorithm. These additional terms may compromise the convergence properties of the IBP algorithm, whereas the SD (and others) approach performed directly on the ML optimization problem assures convergence.

According to the above discussion, therefore, the new approach has thus several benefits when compared to the IBP method, as follows.

1) There is a freedom to choose faster iterative algorithms (such as the CG) to the quadratic optimization problem.

2) Convergence is assured for arbitrary motion charac-teristic, linear space variant blur, different decimation factors for the measurements, and different additive noise statistics.

3) Locally adaptive regularization can be added in a simple fashion, with improved overall performance.

B. The POCS Method

The approach taken in [34]–[36] is the direct application of the POCS method for the restoration of superresolution image. The suggested approach did not use the smoothness constraint as proposed here, and chose to use the distance measure in order to get simpler projection operators. In the sequel, we have presented the bounding ellipsoid method as a tool to relate the POCS results to the stochastic estimation methods. We have seen that applying only ellipsoids as constraints gives a very similar result to the ML and the MAP methods [33]. In [34]–[36], it is suggested to add only the amplitude constraint given in to the trivial ellipsoid constraints. We have shown that instead, we can suggest a hybrid method that has a unique solution, and yet is very simple to implement.

C. The Map Method with Huber–Markov Prior

The MAP approach with the Huber–Markov prior was suggested by Schultz and Stevenson [37]. Their approach starts with a linear model describing the relationship between the measurements and the required higher resolution image. This model is very similar to ours, given in (2.2). However, they restrict their treatment to simple uniform blur, and the measurements noise is assumed to be i.i.d. Gaussian vector, with variance which linearly decays as a function of the image index, related to the center index. This property gives higher influence to near images, and low influence to distant ones. As we have seen above, the MAP estimator suggests some sort of regularization, originated from stochastic modeling. In the Huber–Markov prior, this regularization is a Gibbs prior that penalizes high activity regions. No attempt is made to adopt this penalty to be locally varying, according to the image content. The Huber–Markov prior is simply a quadratic function for low activity values, and linear for higher values.

As such, the overall resulting minimization problem becomes nonquadratic, and is typically more complicated to solve. According to the above discussion, our new approach thus has several advantages when compared to the MAP–Huber method given in [37], listed below.

1) In our approach, relatively simple and efficient iterative algorithms can be applied, with assured convergence, whereas the MAP–Huber method results in a more complicated optimization problem.

2) The MAP–Huber method as given in [37] treats only simple blur and white noise.

3) Locally adaptive regularization can be added in a simple fashion, with improved overall performance.

V. Conclusion:

The SR imaging has been one of the fundamental image processing research areas. It can overcome or compensate the inherent hardware limitations of the imaging system to provide a more clear image with a richer and informative content. It can also be served as an appreciable front-end pre-process- ing stage to facilitate various image processing applications to improve their targeted terminal performance. In this sur-vey paper, our goal is to offer new perspectives and out looks of SR imaging research, besides giving an updated overview of existing SR algorithms. It is our hope that this work could inspire more image processing researchers endeavoring on this fascinating topic and developing more novel SR tech-niques along the way

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