Super-Resolution Reconstruction and Its Future Research Direction

Vorapoj Patanavijit

Department of Computer and Network Engineering, Faculty of Engineering
Assumption University, Bangkok, Thailand
E-mail: <Patanavijit@yahoo.com>

Abstract

During this decade, the enlargement in the extensive use of digital imaging technologies in consumer (e.g., digital video) and other markets (e.g. security and military) has brought with it a simultaneous demand for higher-resolution (HR) images. The demand for such images can be partially met by algorithmic advances in Super-Resolution Reconstruction (SRR) technology in addition to hardware development. Not only do such HR images give the viewer a more pleasing picture but also offer additional details that are significant for subsequent analysis in many applications. SRR algorithm is considered to be one of the most promising techniques that can help overcome the limitations due to optics and sensor resolution. In general, the problem of super-resolution can be expressed as that of combining a set of aliased, noisy, low-resolution, blurry images to produce a higher resolution image or image sequence. The idea is to increase the information content in the final image by exploiting the additional spatio-temporal information that is available in each of the LR images. Consequently, the major advantage of the SRR algorithm is that it may cost less and the existing LR imaging systems can be still utilized. The SRR algorithm is proved to be useful in several practical cases where multiple frames of the same scene can be obtained, including medical imaging, satellite imaging, and video applications.

Keywords: *Digital image processing, digital image reconstruction, higher-resolution images, algorithmic advances.*

1. Introduction

This section is not meant to provide a review of the completed literature on image restoration but to provide some perspective on how SRR (Super-Resolution Reconstruction) algorithms grew out of the existing body of research. The spatial resolution that represents the number of pixels per unit area in an image is the principal factor in determining the quality of an image (Kang and Chaudhuri 2003; Ng and Bose 2003; Park, *et al*. 2003; Rajan, *et al*. 2003). With the development of image processing applications, there is a great demand for high-resolution (HR) images since HR images offer not only the viewer a pleasing picture but also additional details that are important for the analysis in many applications. The most direct solution to increase spatial resolution is to reduce the pixel size (i.e., increase the number of pixels per unit area) by sensor manufacturing techniques. As the pixel size decreases, however, the amount of light available also decreases. It generates shot noise that severely degrades the image quality. To reduce the pixel size without suffering the effects of shot noise, therefore, there exists the limitation of the pixel size reduction, and the optimally limited pixel size is estimated at about 40 μm^2 for a 0.35 µm CMOS processor (Kang and Chaudhuri 2003; Park, *et al*. 2003). The current image sensor technology has almost reached this level. Another approach for enhancing the spatial resolution is to increase the chip size, which leads to an increase in capacitance. Since large capacitance makes it difficult to speed up a charge transfer rate, this approach is not considered effective. The high cost for high precision optics and image sensors is also an important concern in many commercial applications regarding HR imaging therefore many digital image restoration techniques have been proposed since 1970s (Banham and Katsaggelos 1997; Gonzalez and Woods 1992).

Based on the number of observed frames, image restoration techniques are broadly categorized into two classes. Specifically, the categorization is into the classes of single-frame and multi-frame restoration methods. The classical image restoration problem is concerned with restoration of a single output image from a single degraded observed image and the literature on the restoration of a single input frame is extensive and spans several decades (Kundur and Hatzinakos 1996, 1996b, 1998; Lanteri, *et al*. 2001; Banham and Katsaggelos 1997; Gonzalez and Woods 1992; Gunturk, *et al*. 2002; Black and Rangarajan 1996; Black, *et al*. 1997, 1998; Black and Sapiro 1999; Demoment 1989; Kondi, *et al*. 2002). Although the field of single frame image restoration appears to have matured, digital video has raised many new restoration problems for image processing researchers (Wang, *et al*. 2001). Since video usually consists of a sequence of similar, though not identical frames, it becomes possible to utilize the inter-frame motion information in processing the video data. This led to the development of image sequence processing techniques such as motion estimation (Stiller and Konrad 1999; Patras and Worring 2002; Namuduri 2004; Chaudhuri and Taur 2005; Zhu and Ma 2000; Dang, *et al*. 1995; Jing and Chau 2004; and Wang, *et al*. 2001), image sequence interpolation (Gonzalez and Woods 1992), image registration (Fitzgibbon 2001; Kundur and Hatzinakos 1996, 1996b; and Zitová and Flusser 2003) and standards conversion (Wang, *et al*. 2001). Consequently, image restoration researchers also recognized the potential of image restoration in increasing spatial resolution using the information totally contained in an image sequence as compared with that available from a single image. This led naturally to algorithms that apply motion compensation and image restoration techniques to produce high-quality and high-resolution still images from image sequences called SRR (Super-Resolution Reconstruction).

SRR algorithms investigate the relative motion information between multiple corrupted low-resolution (LR) images or a video sequence and increase the spatial resolution by fusing them into a single frame. In doing so, it also removes the effect of possible blurring and noise in the LR images. In summary, the SRR algorithm estimates an HR image with finer spectral details from multiple LR observations degraded by blur, noise, and aliasing (Segall, *et al*. 2003; Rajan, *et al*. 2003; Kang and Chaudhuri 2003; Ng and Bose 2003; and Park, *et al*. 2003).

Therefore, the major advantage of this approach is that the cost of implementation is reduced and the existing LR imaging systems can still be utilized. Hence, applications for the techniques of SRR from image sequences grow rapidly as the theory gains exposure. Continuing researches and the availability of fast computational machineries have made these methods increasingly attractive in applications requiring the highest restoration performance. SRR techniques have already been applied to problems in a number of applications such as satellite imaging, astronomical imaging, video enhancement (Callicó, *et al*. 2003; Jiang, *et al*. 2003; Zibetti and Mayer 2005) and restoration, video standards conversion, confocal microscopy, digital mosaicing, aperture displacement cameras, medical computed tomographic imaging, diffraction tomography, video freeze frame, hard copy and concealed weapon detection (Chen, *et al*. 2005).

2. Introduction of SRR Algorithm

In SRR, typically, the LR images represent different “looks” at the same scene (Park, *et al*. 2003). 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 thus 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, 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 a HR image. To obtain

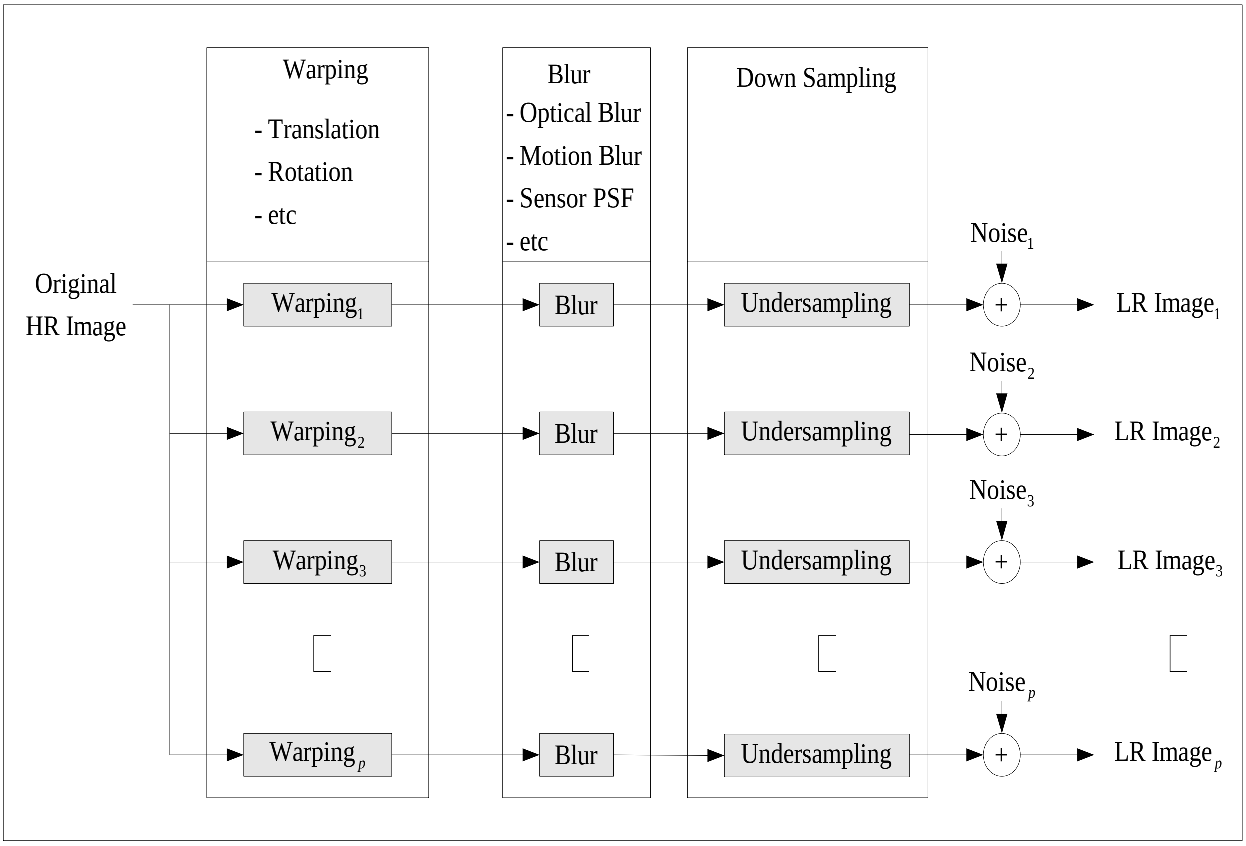

Fig. 1. Imaging system or observation model.

different looks at the same scene, some relative 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. These scene motions can occur due to the controlled motions in imaging systems, e.g., images acquired from orbiting satellites. The same is true of uncontrolled motions, e.g., movement of local objects or vibrating imaging systems. If these scene motions are known or can be estimated within sub-pixel accuracy and if these LR images are combined, then SRR is possible.

2.1 Imaging System, or Observation Model

Transitionally, imaging systems, or observation models, can be broadly divided into the models for still images and for video sequence. To present a basic concept of SR reconstruction techniques, the imaging system for still images is shown in Fig. 1, since it is rather straightforward to extend the still image scene motions must exist from frame model to the video sequence model (Park, *et al*. 2003; and Borman 2004).

The warping process is caused by the motion that occurs during the image acquisition is represented by warping processes and this motion may contain global or local translation, rotation, and so on. Because this motion information is typically unknown, it is needed to estimate the scene motion for each frame with reference to one particular frame. Moreover, the warping process performed on HR image is actually defined in terms of LR pixel spacing when being estimated. Thereby, this step requires interpolation when the fractional unit of motion is not equal to the HR sensor grid (Stiller and Konrad 1999; Bradshaw and Kingsbury 1997; Patras and Worring 2002; Wegger 2000; Namuduri 2004; Milanfar 1999; Vandewalle, *et al*. 2004; Vandewalle, *et al*. 2005; Vandewalle, *et al*. 2006; Zhu and Ma 2000; Dang, *et al*. 1995; Patanavijit and Jitapulkul 2006; Patanavijit, *et al*. 2007; Beauchemin and Barron 1995; and Ben-Ezra and Nayar 2004).

The blur process may be caused by an optical system (e.g., out of focus, diffraction limit, aberration, etc.), relative motion between the imaging system and the original scene, and the point spread function (PSF) of the LR sensor. The optical or motion blur in single image restoration applications is usually considered however the finiteness of a physical dimension in LR sensors in the SRR is an important factor of blur. In the use of SRR algorithms, the characteristics of the blur are assumed to be known. However, if it is difficult to obtain this information, blur identification should be incorporated into the reconstruction procedure (Anconelli 2003; and Bascle, *et al.* 1996).

The down-sampling process often generates aliased LR images from the warped and blurred HR image due to memory and data transferring limitation.

Finally, the observed image may be corrupted by noise for several reasons such as shot noise (by electronic devices).

2.2 Concept of SRR Algorithm

Most of the explored SRR algorithms consist of the three stages (Fig. 2). These steps can be implemented separately or simultaneously according to the reconstruction methods adopted.

First, the SRR algorithm receive several low-resolution corrupted images as the inputs then the registration or estimation process estimate the relative shifts between LR images compared to the reference LR image with fractional pixel accuracy. Obviously, accurate sub-pixel motion estimation is a very important factor in the success of the SRR algorithm. Since the shifts between LR images are arbitrary, the registered HR image will not always match up to a uniformly spaced HR grid. Thus, non-uniform interpolation is necessary to obtain a uniformly spaced HR image from a composite of non-uniformly spaced LR images. Finally, image restoration is applied to the up-sampled image to remove blurring and noise.

3. Review of SRR

Based on the observation model that is presented in previous section, the relevant research papers, published in the conferences and journals are comprehensively reviewed and are broadly categorized into two classes (Patanavijit and Jitapunkul 2007). Specifically, the categorization is into the classes of reconstruction-based SRR algorithm and Recognition-Based SRR algorithm (or hallucination).

3.1 Reconstruction-Based SRR Algorithm

This reconstruction-based SRR algorithm doesn't require images for training therefore this algorithm doesn't depend on observed images but Reconstruction-based approach inherits limitations when magnification factor increases.

3.1.1 Frequency Domain Approach: The frequency domain approach makes explicit use of the aliasing that exists in each LR image to reconstruct an HR image.

The Super-Resolution Reconstruction (SRR) idea was first presented by Huang and Tsai (1984). They used the frequency domain approach to demonstrate the ability to reconstruct one improved resolution image from several downsampled noise-free versions of it, based on the spatial aliasing effect. Next, a frequency domain recursive algorithm for the restoration of super-resolution images from noisy and blurred measurements was proposed

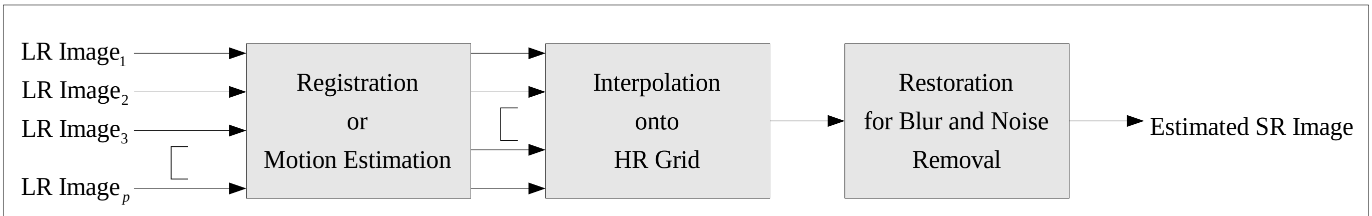

Fig. 2. Basic structure of super-resolution reconstruction (SRR).

by Kim, *et al*. (1990). The algorithm using a weighted recursive least squares algorithm, is based on sequential estimation theory in the frequency-wave number domain, to achieve simultaneous improvement in signal-to-noise ratio and resolution from available registered sequence of low-resolution noisy frames. Kim and Su (1993) also incorporated explicitly the deblurring computation into the high-resolution image reconstruction process because separate deblurring of input frames would introduce the undesirable phase and high wave number distortions in the DFT of those frames. Subsequently, Ng and Bose (2002) proposed the analysis of the displacement errors on the convergence rate to the iterative approach for solving the transform based preconditioned system of equation hence it is established that the use of the MAP, L2 Norm or H1 Norm regularization functional leads to a proof of linear convergence of the conjugate gradient method in terms of the displacement errors caused by the imperfect sub-pixel locations. Park, *et al*. (2004) proposed adaptive high-resolution image reconstruction of DCT-based compressed images. Later, Bose, *et al*. (2006) proposed the fast SRR algorithm, using MAP with MRF for blurred observation. This algorithm uses the reconditioned conjugated gradient method and FFT.

Although the frequency domain methods are intuitively simple and computationally cheap, the observation model is restricted to only global translational motion and LSI blur. Due to the lack of data correlation in the frequency domain, it is also difficult to apply the spatial domain a priori knowledge for regularization.

3.1.2 POCS Approach (Projection onto Convex Sets): The POCS approach describes an alternative iterative approach to incorporating prior knowledge about the solution into the reconstruction process. With the estimates of registration parameters, this algorithm simultaneously solves the restoration and interpolation problem to estimate the SR image (Combettes and Civanlar 1991; Combettes 1993).

The POCS formulation of the SRR was first suggested by Stark and Oskoui (1989). Their method was extended by Tekalp, *et al*. (1992) to include observation noise. Although POCS is simple and can utilize a convenient inclusion of a priori information, this method has the disadvantages of non-uniqueness of solution, slow convergence and a high computational cost. Next, Patti and Altunbasak (2001) proposed a SRR (Super-Resolution Reconstruction) using ML estimator with POCS-based regularization and Altunbasak, *et al.* (2002) proposed a Super-Resolution Reconstruction (SRR) for the MPEG sequences. They proposed a motion-compensated, transform-domain super-resolution procedure that directly incorporates the transform-domain quantization information by working with the compressed bit stream. Later, Gunturk, *et al*. (2004) proposed a ML super-resolution with regularization based on compression quantization, additive noise and image prior information in 2004. Next, Hasegawa, *et al*. (2005) proposed iterative SSR using the Adaptive Projected Sub-gradient method for MPEG sequences.

3.1.3 Regularized ML Approach: Typically, the SRR algorithm is an ill-posed problem due to an insufficient number of LR images and ill-conditioned blur operators. Procedures adopted to stabilize the inversion of ill-posed problem are called regularization. In this section, deterministic and stochastic regularization approaches for SRR algorithm are presented. Traditionally, constrained least squares (CLS) (Haykin 2002) and maximum a posteriori (MAP) SR image reconstruction methods are introduced (Vaseghi 1996).

The MRF or Markov/Gibbs Random Fields are proposed and developed for modeling image texture during 1990-1994 (Elfadel and Picard 1990, 1993, 1994; Picard and Elfadel 1994; Picard, *et al*. 1991; Picard 1992; Popat and Picard 1993, 1994). Due to MRF (Markov Random Field) that can model the image characteristic especially on image texture, Bouman and Sauer (1993) proposed the single image restoration algorithm using MAP estimator with the GGMRF (Generalized Gaussian-Markov Random Field) prior. Later, Stevenson, *et al*. (1994) proposed the single image restoration algorithm using ML estimator with the Discontinuity Persevering Regularization. Schultz and Stevenson (1994) proposed the single image restoration algorithm using MAP estimator with the HMRF (Huber-Markov Random Field) prior. Next, the Super-Resolution Reconstruction algorithm using MAP estimator (or the Regularized ML estimator), with the HMRF prior was proposed by Schultz and Stevenson (1996). The blur of the measured images is assumed to be simple averaging and the measurements additive noise is assumed to be independent and identically distributed (i.i.d.) Gaussian vector. Pan and Reeves (2006) proposed single image MAP estimator restoration algorithm with the efficient HMRF prior using decomposition-enabled edge-preserving image restoration in order to reduce the computational demand.

Typically, the regularized ML estimation (or MAP) is used in image restoration therefore the determination of the regularization parameter is an important issue in the image restoration. Thompson, *et al*. (1991) proposed the Methods of choosing the smoothing parameter in image restoration by regularized ML. Next, Mesarovic, *et al*. (1995) proposed the single image restoration using regularized ML for unknown linear space-invariant (LSI) point spread function (PSF). Subsequently, Geman and Yang (1995) proposed single image restoration using regularized ML with robust nonlinear regularization. This approach can be done efficiently by Monte Carlo Methods, for example by annealing FFT domain using Markov chain that alternates between (global) transitions from one array to the other. Later, Kang and Katsaggelos (1995) proposed the use of a single image regularization functional, which is defined in terms of restored image at each iteration step, instead of a constant regularization parameter and Kang and Katsaggelos (1997) proposed regularized ML for SRR, in which no prior knowledge of the noise variance at each frame or the degree of smoothness of the original image is required. Molina (1995) and Molina, *et al*. (1999) proposed the application of the hierarchical ML with Laplacian regularization to the single image restoration problem and derived expressions for the iterative evaluation of the two hyper-parameters (regularized parameter) applying the evidence and maximum a posteriori (MAP) analysis within the hierarchical regularized ML paradigm. Molina, *et al*. (2003) proposed the multi-frame super-resolution reconstruction using ML with Laplacian regularization. The regularized parameter is defined in terms of restored image at each iteration step. Next, Rajan and Chaudhuri (2003) proposed super-resolution approach, based on ML with MRF regularization, to simultaneously estimate the depth map and the focused image of a scene, both at a super-resolution from its defocused observed images. Subsequently, He and Kondi (2004, 2004b) proposed image resolution enhancement with adaptively weighted low-resolution images (channels) and simultaneous estimation of the regularization parameter and He and Kondi (2005) proposed a generalized framework of regularized image/video Iterative Blind Deconvolution/Super-Resolution (IBD-SR) algorithm using some information from the more matured blind Deconvolution techniques form image restoration. Later, He and Kondi (2006) proposed SRR algorithm that takes into account inaccurate estimates of the registration parameters and the point spread function. Vega, *et al*. (2006) proposed the problem of de-convolving color images observed with a single coupled charged device (CCD) from the super-resolution point of view. Utilizing the regularized ML paradigm, an estimate of the reconstructed image and the model parameters is generated.

Elad and Feuer (1997) proposed the hybrid method combining the ML and non-ellipsoid constraints for the super-resolution restoration and Elad and Feuer (1999) proposed the adaptive filtering approach for the Super-Resolution Reconstruction. Next, Elad and Feuer (1999b) proposed two iterative algorithms, the R-SD and the R-LMS, to generate the desired image sequence at the practically computational complexity. These algorithms assume the knowledge of the blur, the down-sampling, the sequences motion, and the measurements noise characteristics, and apply a sequential reconstruction process. Subsequently, the special case of Super-Resolution Reconstruction (where the warps are pure translations, the blur is space invariant and the same for all the images and the noise is white) are proposed by Elad and Hel-Or (2001) for a fast Super-Resolution Reconstruction. Later, Nguyen (2000) and Nguyen, *et al*. (2001) proposed fast SRR algorithm using regularized ML by using efficient block circulant preconditioners and the conjugate gradient method. Elad (2002) proposed the Bilateral Filter theory, showed how the bilateral filter can be improved and extended to treat more general reconstruction problems. Consequently, the alternate super-resolution approach, L1 Norm estimator and robust regularization based on a Bilateral Total Variance (BTV), was presented by Farsiu, *et al*. (2004, 2004b). This approach performance is superior to what proposed earlier in and this approach has fast convergence but this SRR algorithm effectively apply only on AWGN models. Next, Farsiu, *et al*. (2006) proposed a fast SRR of color images using ML estimator with BTV regularization for luminance component and Tikhonov regularization for chrominance component. Subsequently, Farsiu, *et al*. (2006b) proposed the dynamic super-resolution problem of reconstructing a high-quality set of monochromatic or color super-resolved images from low-quality monochromatic, color or mosaiced frames. This approach includes a joint method for simultaneous SR, deblurring and Demosaicing. It takes into account practical color measurements encountered in video sequences. Later, Patanavijit and Jitapunkul (2006) proposed the SRR using a regularized ML estimator with affine block-based registration for the real image sequence. Moreover, Rochefort, *et al*. (2006) proposed super-resolution approach based on regularized ML for the extended original observation model devoted to the case of non-isometirc interframe motion such as affine motion.

3.1.4 Nonuniform Interpolation Approach: This approach is the most intuitive method for SR image reconstruction. The three stages presented in Fig. 2 are performed successively in this approach: (i) estimation of relative motion, i.e., registration; (ii) nonuniform interpolation to produce an improved resolution image; and (iii) deblurring process.

During 2004 to 2006, Vandewalle, *et al*. (2004, 2005, 2006) have proposed a fast super-resolution reconstruction based on a non-uniform interpolation using a frequency domain registration. This method has low computation and can be used in the real-time system but the degradation models are limited, therefore, this algorithm can apply on few applications.

3.2 Recognition-Based SRR Algorithm (or Hallucination)

This recognition-based SRR algorithm require images for training therefore this algorithm depend on observed images but this algorithm have high performance when magnification factor increases. (Capel and Zisserman 2001; and Lin and Shum 2004).

3.2.1 Weighted Sum (WS) Filter Approach: Barner *et al*. (1999) proposed the single image restoration algorithm (recognition-based) using Hard Partition based Weighted Sum (HP-WS) filter. Observed image is partition into several blocks and each block is quantized in order to select the most proper filter coefficient for that block to restoration. The weights (or filter coefficients) is turned by train on a representative image and the two-state suboptimal training is proposed to determine optimizing weights (or filter coefficients). Although this algorithm can be effectively applied on the image but an analytical solution for the global optimization is difficult to obtain due to the nondifferentiable HP-WS filter function.

Alam, *et al.* (2000) proposed the SRR algorithm (the interpolation-restoration techniques) for the infrared images. The gradient-based registration is used for each observed LR images and a weighted nearest-neighbor approach for placing the frame onto a uniform grid to form a high-resolution image. Subsequently, the Wiener filter is used for deblurring the final high-resolution image.

Later, Lin, *et al*. (2005) proposed the single image restoration algorithm (recognition-based) using Subspace HP-WS (S-HPWS) filter. The observation vectors into a subspace using PCA (Principal Component

Analysis) in order to reduce the computational burden especially for large window sizes. Consequently, the performance is enhanced due to improved partitioning size and the computation time of the S-HPWS is less than half of that of the HP-WS for training and testing.

Due to the non-differentiable characteristic, the global optimization of HP-WS is difficult to obtain. Consequently, Lin, *et al*. (2006) proposed a novel radial basis function interpretation of the Soft Partition based Weighted Sum (SP-WS) filters and present an efficient optimization procedure based on the gradient method (both quasi-Newton method and steepest descent method).

Next, Shao and Barner (2006) proposed the single image restoration algorithm (recognition-based) using Soft Partition based Weighted Sum (SP-WS) filter. Thus, an analytical solution for the global optimization is easily to obtain due to the differentiable SP-WS filter function. Moreover, they compared the proposed SP-WS solution and HP-WS solution computed by two-state suboptimal training and by GA algorithm.

Narayanan, *et al*. (2007) proposed the fast recognition-based SRR algorithm (the interpolation-restoration techniques) using Hard Partition based Weighted Sum (HP-WS) filter. Due to computational complexity, the HP-WS filter is incorporate in this algorithm instead of SP-WS filter. Hence, HP-WS filters are employed to simultaneously perform non-uniform interpolation and perform de-convolution of the system PSF.

Subsequently, Hardie (2007) proposed the fast SRR algorithm using the fast recognition-based SRR algorithm (the interpolation-restoration techniques) using Adaptive Wiener Filter. The positions of the LR pixels are not quantized to a finite grid as with some previous techniques and the weights (or filter coefficients) for each HR pixels are designed to minimize the MSE and they depend on the relative positions of the surrounding LR pixels. The parametric statistical model is used for these correlations that ultimately define the filter weights.

3.2.2 Statistical Approach: Baker and Kanade (2002) proposed another super-resolution algorithm (hallucination or recognition-based super-resolution) that attempts to recognize local features in the low-resolution image and then enhances their resolution in an appropriate manner. Due to the training data base, therefore, this algorithm performance depends on the image type (such as face or character) and this algorithm is not robust enough to be sued in typical surveillance video. Next, Sun, *et al*. (2003) proposed hallucination super-resolution (for single image) using regularization ML with primal sketches as the basic recognition elements. Later, Jai and Gong (2008) proposed Generalized Face Super-Resolution. This algorithm uses Tensor Space to represent face images and can be applied to multi-model cases such as smiling or angry images.

4. Concluding Remarks and Future Research

This article aims to present the concept of SRR technology by providing an overview of existing SRR algorithms. The article also categorizes and reviews the SRR researches for each category approach in order to assist the proper understanding of the readers. From this comprehensive literature review, although numerous SRR researches are proposed, it can be deduced that it is necessary to extend the current SRR algorithms to real-world imaging systems, as follows:

1) Color imaging system is slightly considered by SRR research community but a more careful reconstruction method which reflects the characteristic of color is needed. The important problem in color SRR is to analyze the characteristic of a color filter array and color interpolation procedure and take into account intercorrelation between color components in the reconstruction procedure (Kimmel 1999; Capel 2001).
2) Compressing imaging system (MPEG/JPEG) that has a special blur and noisy characteristic. Few SRR algorithms have addressed resolution enhancement of compressed video sequences. Compression artifacts can dramatically

decrease the performance of any SRR algorithms. Moreover, consideration of compression color artifacts in designing novel multiframe demosaicing algorithms is a part of the ongoing work. (Schilling and Cosman 2003; Robertson 1998; Hasegawa, *et al.* 2005)

3) Imaging system that is corrupted by real noise model (not a simple Gaussian noise model) such as Poisson noise, Salt & Pepper or Speckle.
4) The performance of SRR algorithm depends on the accuracy of the registration process. Therefore, more realistic and higher accuracy registrations are still required for higher accuracy results from the SRR algorithms. (Fitzgibbon 2001; Lim 2002)
5) Traditionally, the blurring function is unknown, hence, one important extension for the SRR algorithms is the incorporation of blur identification algorithms in the SRR algorithm because many single-frame blind deconvolution algorithms have been suggested in the last two decades.
6) Moreover, computational resources are becoming progressively more powerful and cheaper, therefore, this makes it feasible to implement algorithms which were previously prohibitive in terms of their computational complexity.

SRR algorithms form one of the most spotlighted research areas during this decade, because they can overcome the inherent resolution limitation of the imaging systems and improve the performance of most digital image processing applications. Consequently, the author hopes that this article may create interest in this area as well as motivation to further develop relevant SRR techniques.

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