ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 2, Issue 7, July 2013

IMAGE SUPER-RESOLUTION

Priyadarshini D Shinde[*], Dr. S.L. Nalbalwar [**]

[*] Department of E & TC, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India.

[**]Department of E & TC, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India.

Abstract- High Resolution (HR) images are demanded everywhere in the fields like medical imaging, remote sensing and surveillance etc. Signal processing techniques can be used to obtain High Resolution (HR) images from aliased Low Resolution (LR) Images, which can make significant use of existing technology. The method to obtain HR image from aliased Low Resolution (LR) image(s) is called as Image Super-Resolution(ISR). This paper broadly classifies ISR as single image SR and multiple image SR. single image SR with the help of sparse representation and different algorithms of multiple image SR are discussed.

Index Terms- Multisurface fitting , Projection onto convex sets(POCS),Super-resolution reconstruction (SRR),Sparse representation.

I. INTRODUCTION

The central aim of Super-Resolution (SR) is to obtain HR image from LR image(s). High resolution image can offer more details of original scene as density of pixel is high. To improve the performance of pattern recognition in computer vision there is need for high resolution image(s). High resolution is of importance in medical imaging for diagnosis. Surveillance, forensic and satellite imaging applications require zooming of a specific area of interest in the image where high resolution becomes important. whereas high resolution images are not always available due to expensive setup. also it may not always be possible to reach the requirement of desired resolution due to the sensor limitations and optics manufacturing technology. To overcome these limitations signal processing techniques can be used effectively and efficiently. This gives rise to the concept of image super-resolution. Advantage of working with signal processing algorithm is that it may cost less and we can utilize existing low resolution system.

High resolution images are becoming very useful for doctors to make a correct diagnosis. Development in space technology is able to send more platforms in space to survey the earth. Space target recognition is made with orbit and radio signal recognition. Super-resolution reconstruction (SRR) techniques can be used to study images of space objects. For our safety it is necessary to know the danger of the planetoid ,so there is need to detect all the space objects near to the earth. Super-resolution techniques can be helpful in such case [5]. With the help of HR satellite images it became easy to distinguish similar objects. SRR technique are becoming useful in converting NTSC video signal to an HDTV video signal. SR techniques are becoming useful in medical imaging like Computational Tomography (CT) and Magnetic Resonance Imaging (MRI). Combined use of image restoration and image reconstruction techniques can be made to improve image quality. To improve fidelity, image restoration technique can be used . image restoration algorithms are helpful to remove blur, noise, aliasing effects but they does not change size of an image [4], [5]. Whenever it is necessary to zoom an image, image reconstruction techniques are becoming helpful. In other words super-resolution reconstruction tries to generate missing high frequency components and remove noise and blur effects.

Super-Resolution Reconstruction can be performed either with the help of single image or set of multiple images. Multiple LR images which represents different looks of the same scene can be used to obtain HR image. Multiple images of the same scene can be obtained with the help of one camera with several captures or with several cameras located at different locations or with video sequence. LR images should be aliased and shifted with subpixel precision. If they are shifted with integer units then each image contains same information. Thus no new information can be obtained which will be useful to reconstruct an image. Within LR images if aliasing is present and if they have different subpixel shifts then each image cannot be obtained from other. In such case new information obtained from each image can be used to obtain HR image. While recording a digital image there is loss of spatial resolution due to aliasing, motion blur, optical distortion, noise etc.

Thus even main goal of SRR is to reconstruct an HR image from aliased LR images it also covers restoration technique to obtain good quality image from blurred, noisy LR images[2].

II. CLASSIFICATION

Super-resolution methods can be broadly classified as single image super-resolution and multiple image super-resolution.

1. Single image super-resolution

This paper presents an approach to single-image Super-resolution, based on sparse signal representation. Research in technology has reached to the suggestion that, image patches can be well represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary. With this observation, we seek a sparse representation for each patch of the low-resolution input, and then we can make use of these coefficients of this representation to generate the high-resolution image. It is observed from theoretical results that under mild conditions, the sparse representation can be correctly recovered from the downsampled signals. By jointly training two dictionaries for the low and high-resolution image patches, we can enforce the similarity of sparse representations between the low resolution and high resolution image patch pair with respect to their own dictionaries. To generate a high resolution image patch , the sparse representation of a low resolution image patch can be applied with the high resolution image patch dictionary. more compact representation of the patch pairs is the learned dictionary pair compared to previous approaches, which simply sample a large amount of image patch pairs [7], which reduces the computational cost.

Some super-resolution techniques perform image super-resolution with the help of single image using database of related or unrelated images. Although estimation which is based on Nearest neighbor algorithm is poor, when complex or high dimensional data is considered learning based approaches uses these algorithms to obtain HR image from single LR image [6]. On the basis of distance measurement similar images are taken into consideration. Performance of nearest neighbor algorithm can be improved with the help of local learning method[6]. Learning based algorithms works in two phases viz. training phase and super-resolution phase. In the former one training set is generated by comparing the training samples and a given test sample. In later one comparison is made between each patch of the LR image and the stored LR patches, and the high-resolution patch corresponding to the nearest low-resolution patch. output is taken by satisfying certain spatial neighborhood compatibility using Markov network.

2. Multiple image super-resolution

Some Image super-resolution algorithms with multiple images are discussed below.

2.1 Iterated back-projection

Similar approach to the one which is used in tomography, Irani and Peleg formulated the iterative back-projection (IPB) algorithm for super-resolution. In Computer-Aided Tomography (CAT), from 1-D projections along many directions the image of a 2-D object is reconstructed. In a similar way, the HR image ($\hat{F}$) is estimated by consecutively back projecting the error (difference) between simulated LR images via imaging model and the observed LR images ($\hat{G}_i$). Starting with an initial estimate $\hat{F}_0$ for the HR image, the back-projection process is repeated iteratively for each incoming LR image.
For the ith inbound LR image, the basic update equation can be written as:

$$\begin{aligned}\hat{F}^i &= \hat{F}^{i-1} + H_{BP}(G_i - \hat{G}_i)\\ &= \hat{F}^{i-1} + H_{BP}(G_i - A_i\hat{F}^{i-1})\end{aligned} \quad (1)$$

where H_{BP} is the back-projection filtering operator which performs the projection of the error image on the HR estimate. The matrix H_{BP} integrates the motion compensation and the interpolation filter h_{bp}, consecutively. Unlike the imaging blur which occurs due to h_{psf}, the back-projection filter (h_{bp}) can be chosen freely. If we assume h_{bp} is Gaussian with parameter σ_{bp}, then the sharpness of the final result may be controlled by selecting a small value for σ_{bp}. Advantage of this algorithm from a practical point of view is that it can handle incoming LR images without the need of buffering, which significantly lowers the memory use, still producing competitive results. Absence of a regularization step is one of the difficulty in this filtering approach. It means that the algorithm may converge to several possible solutions, and keeps oscillating among some of these. As the iterations proceeds, the final result is influenced more by the latest images. In terms of speed of convergence or stability, the choice of the initial estimate does not significantly influence the performance of the algorithm. It may influence on the one of the possible solutions which is reached first. It is good to choose the initial estimate as the average of the motion-compensated LR images, which normally leads to smoother solution.

2.2 projection onto convex sets algorithm

Most popular algorithms among iterative HR reconstruction techniques are Projection onto

ISSN: 2278 – 7798
International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 2, Issue 7, July 2013

Convex Sets (POCS) and Maximum A Posteriori (MAP) estimation[1].

The POCS provides an iterative approach to incorporate prior knowledge about the solution into the reconstruction process. POCS provides simultaneous solution to restoration and interpolation problem to estimate the SR image (Combettes and Civanlar 1991; Combettes 1993) with the help of estimates of registration parameters [3].The POCS method was first suggested by Stark and Oskoui (1989). It was extended by Tekalp, *et al*. (1992) to include observation noise. This method is simple and can make use of priori information in a more convenient way. Disadvantage of this method is that solution obtained with this method may not be unique. It has slow convergence rate and a high computational cost. Patti and Altunbasak (2001) used ML estimator with POCS-based regularization and Altunbasak, *et al.* (2002) proposed SRR for the MPEG sequences. They proposed a motion-compensated, transform-domain super-resolution that directly gives the transform-domain quantization information by working with the compressed bit stream. Next, Gunturk, *et al*. (2004) proposed ML SRR with regularization which is based on compression quantization, additive noise and image prior information. Later, Hasegawa, *et al*. (2005) proposed iterative Super-resolution using the Adaptive Projected Sub-gradient method for MPEG sequences [3].

2.3 Maximum *a-posteriori*

Maximum *a-posteriori* approach (MAP) treats the super-resolution problem as a statistical estimation problem. By maximizing the *a-posteriori* conditional probability, the Bayesian formulation solves for the probability density function (PDF) of the original image. The MAP formulation provides an easy method to integrate *a-priori* knowledge regarding the solution as compared with the Maximum Likelihood (ML) solution. This priori knowledge considerably helps to regularize the inverse problem.

2.4 Interpolation based SR using multisurface fitting

Interpolation based methods treat SR as a nonuniform interpolation problem. First idea of interpolation using Delaunay triangulation is proposed in [8].

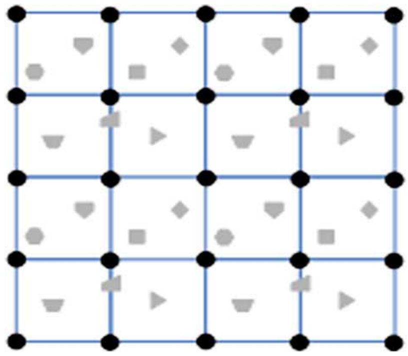

Fig. 1. Illustration of the problem of interpolation-based SR. The “circles” grid nodes represent the HR pixels to be estimated. The LR pixels are represented by other shapes. Different shapes represent pixels from different LR images.

Basically, the problem of interpolation-based SR is how to convert arbitrarily sampled data to evenly spaced data [1]. After subpixel registration, pixels from different observed LR images are positioned in an HR grid, as shown in Fig. 1.FF

Let, intensity of the HR pixel p_H is the value to be estimated. In the neighborhood of p_H, we have different LR pixels denoted by $p_{L1,\dots}$ $p_{Li,\dots}$ p_{LK}, where K is the number of LR pixels in the neighborhood of p_H. Conventional idea is to fit a surface with local smoothness from a group of LR pixels ($p_{L1,\dots}$ $p_{Li,\dots}$ p_{LK}). The fitted surface can be regarded as the continuous image. Subsequently, the HR pixel p_H is obtained by resampling the surface. This process can be formulated as

$$\Gamma=\Gamma(f(p_{L1}),\dots,\ f(p_{L2}),\dots\ f(p_{Lk}),\ x_{L1,\dots,}\ x_{Li,\dots}\ x_{Lk},\ y_{L1,\dots}y_{Li,\dots}\ y_{Lk}) \qquad (2)$$

$$f(p_H) = S(x_H, y_H, \Gamma) \qquad (3)$$

where Γ represents fitted surface for multipixels $f(p\Phi)$ represents intensity of pixel $p\Phi$, $x\Phi$, $y\Phi$ represents location of pixel $p\Phi$ in abscissas and ordinates of the HR grid, respectively; $S(x\Phi, y\Phi, \Gamma)$ represents operation of sampling the surface Γ at location $(x\Phi, y\Phi)$

Where $\Phi \in \{ H, L_1, \dots L_{i,\dots} L_K\}$

By taking into account the importance of spatial structure information Pham *et al.* introduces a nonuniform interpolation by using the normalized convolution (NC) [9]. Similar to NC, Takeda *et al.* presented steering kernel regression in [10]. Fei Zhou, Wenming Yang proposed a new nonuniform interpolation-based SR method using multisurface fitting. Their idea is to fit one surface for every LR pixel and fuse the multisampling values in maximum a posteriori fashion. As the number of LR pixels is more than that of HR pixels this method represents structure information in a more elaborate way than [9] and [10]. However for the final estimation of HR pixel, more LR pixels contribute effectively. The method gives closed form solution opposite to that of iterative estimations. The method has two advantages, first is that higher order information can be preserved i.e. regarding the preserving of image details the method outperforms other interpolation-based approaches. Second, is that it does not need any artificial hypothesis on image prior unlike the iterative techniques using regularization [1].

III. CONCLUDING REMARKS AND FUTURE SCOPE

This article presents the overview of methods used for image super-resolution reconstruction using single image and multiple images. It also describes advances and drawbacks related to the methods in order to assist the proper understanding of the readers. From this comprehensive literature review, although numerous SRR algorithms are proposed, it can be deduced that it is necessary to extend the current SRR algorithms to real-world imaging systems. Furthermore noise model can also be considered in the current method as an advancement

.

IV. REFERENCES

[1] Fei Zhou, Wenming Yang, and Qingmin Liao, "Interpolation-Based Image Super-Resolution Using Multisurface Fitting", *IEEE Transactions On Image Processing, Vol. 21, No. 7, July 2012.*

[2] S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: A technique overview," *IEEE Signal Process. Mag.*, vol.20, no. 3, pp. 21–36, May 2003.

[3] VorapojPatanavijit. "Super-Resolution Reconstruction and Its Future Research Directions" AU J.T. 12(3): 149-163 (Jan. 2009).

[4] Hang Chang, Dit-Yeung and YiminXiong. " Superresolution through neighbor embedding". CVPR, 01:275-282,2004.

[5] H.Y.Liu , Y.S.Zhang, Song JI, "Study On The Methods Of Super-Resolution Image Reconstruction", *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B2. Beijing 2008.*

[6] M.S. Alam, J.G. Bognar, R.C. Hardie, and B.J. Yasuda, "Infrared image registration and high-resolution reconstruction using multiple translationally shifted aliased video frames," *IEEE Trans. Instrum. Meas.*, vol. 49, pp. 915-923, Oct. 2000.

[7] T. S. Huang and R. Y. Tsay, "Multiple frame image restoration and registration,"in *Advances in Computer Vision and Image Processing*, T. S. Huang, Ed. Greenwich, CT: JAI, 1984, vol. 1, pp. 317–339.

[8] S. Lertrattanapanich and N. K. Bose, "High resolution image formation from lowresolution frames using Delaunay triangulation," *IEEE Trans.Image Process.*, vol. 11, no. 12, pp. 1427–1441, Dec. 2002.

[9] T. Q. Pham, L. J. van Vliet, and K. Schutte, "Robust fusion of irregularly sampled data using adaptive normalized convolution," *EURASIP J. Appl. Signal Process.*, vol. 2006, pp. 83 268-1–83 268-12, 2006.

[10] H. Takeda, S. Farsiu, and P. Milanfar, "Kernel regression for image processing and reconstruction," *IEEE Trans. Image Process.*, vol. 16, no. 4, pp. 349–366, Feb. 2007.

AUTHORS

First Author – Priyadarshini D Shinde , M.Tech, Dr. BabasahebAmbedkarTechnologicalUniversity, Lonere, Maharashtra, India.

Second Author – Dr. S.L. Nalbalwar, Associate Professor, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India.