ADVANCES IN SUPERRESOLUTION USING MAP APPROCH

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Abstract—**Image super resolution is a wide area used for many real life applications such as medical images, video surveillance ect. It is very important to obtain high resolution image from one or many low resolution images for correct identification of decease in medical field. This technique is used to obtain high resolution image from one or many low resolution images which are noisy, blurry and down sampled.Numberof techniques are used to obtain high resolution images among which a technique using MAP (Maximum a posteriori) is a widely used approach which gives high quality output in which regularization parameter plays an important role.This paper gives comparative study of number of approaches used for obtaining high resolution output. Tests on stimulation and actual data are taken. Experimental results gives the comparison of all methods used in which it can be clearly observed that MAP based method provides maximum resolution.**

Keywords- Bicubic interpolation, Adaptive iteration, MAP,Regularizationparameter,Bayesian framework, L-curve,GCV.

I. INTRODUCTION

The techniqes used to obtain High Resolution image from one or more low resolution images is called super resolution.High Resolution (HR) images are used in medical imaging[2] satellite imaging[3] etc. However,due to hardware problem, we get low-resolution (LR) images than HR images.Firstly to tackle super resolution problem many frequency domain methods[4] were used, frequency domain methods are attractive consedering computation power but having limitation that, it is difficult to incorporate the prior information about HR images using frequency domain methods.To overcome these limitations spatial domain methods have been developed, including non uniform interpolation approaches[5] ,the iterative back projection (IBP) approach[6], projection onto convex sets (POCS)[7] approach, deterministic regularized approach[8], maximum likelihood(ML)[9] approach, maximum a posteriori (MAP)[10] approach, joint MAP approach , and hybrid approach[11] **.**

This paper gives the comparative analysis of different methods used for super resolution. The different methods such as Bicubic interpolation, adaptive iteration, L-curve, MAP approach using U-curve were proposed to obtain high resolution images among which MAP is a widely used approach for obtaining high resolution images. The regularization parameter plays a very important role in this MAP model, controlling the proportion between the fidelity and prior information. Selection of this parameter can be done by using many methods, it can be done manually (subjective method) or adaptively, selecting the parameter manually increases the calculations hence this method becomes time consuming hence adaptive methods are preferred. Spatial methods can be divided into two groups.

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One group uses classical methods. For example, the L-curve method, andgeneralized cross validation method (GCV) [12] uses classical methods. The second group uses the general Bayesian framework to estimate parameters and reconstruct HR images simultaneously, obtaining parameters as well as the HR frame in each iteration step. The L-curve and GCV approaches can provide good solutions, but their computational costs are high as these methods uses selection of regularization parameter manually. The Bayesian framework method has a lower computational load, but the optimal reconstruction result is more reliable on some attached parameters and parameter distribution functions, so it cannot be fully adaptive.

The contents of this paper are, 1) Literature survey2) Bicubic Interpolation 3) L-Curve 4) MAP based U-Curve 5)Experimental results.

II. LITRETURE SURVEY

Bicubic Interpolation is a frequency domain technique; here super-resolution technique based on interpolation of the high-frequency subband images obtained by discrete wavelet transform (DWT) and the input image is discussed. In this technique DWT is used to decompose an image into different subband images. Afterword's the high-frequency subband images and the low-resolution input image have been interpolated, followed by combining all these images to generate a new super-resolved image by using inverse discrete wavelet transform (IDWT). This super resolution technique has been tested on various images. The peak signal-to-noise ratio (PSNR) and visual results show the superiority of this technique over the conventional techniques.By using L-Curve we focus on simultaneous blur identification and robust superresolution.The blur is not restricted to be linear shift-invariant and couldnot only be of the linear shift-variant type but also some nonlinearblurs could be accommodated. The optimal tuning parameter may,if desired, be calculated analytically and not by trial-and-error.The U-curve method was first proposed to select the regularization parameter. U-curve method perform better than the L-curve also it provides an interval where the optimal regularization parameter exists, which reduces the computation load in obtaining the optimal regularization parameter. Super resolution problem is more complex problem hence to select regularization parameter more accurately; adaptively we use U-curve method on super resolution model with Laplacian prior. A regularization parameter is a parameter used in some nonlinear iterative method suppresses undesired solutions, by penalizing those with very high spectral frequencies that account for rich small-scale structure. Regularization parameter in is used in some Restoration methods that isfunction of the inverse Signal to Noise ratio the lower the entered SNR, the higher the regularization parameter, and the more the solution will be constrained into the smooth range. Like that, noise amplification is prevented that would generate fake small-scale structure. In short we can say that thisparameterdecides the amount of prior information which should added

Domain	Advantages	Dis – Advantages
Frequency Domain (e.g-BI Method)	Solves Multi-Frame Resolution Problem.	Difficult to incorporate the prior information about images.
Frequency Domain	Solves Multi-Frame Resolution Problem and reduces observation noise and spatial Blurring.	
Frequency Domain	Solves Multi-Frame Resolution Problem and reduces effects of registration.	
Spatial Domain (e.g L-Curve,GCV)	Can incorporate the prior information about images.	

Fig.1 Super resolution Methods.

Methods	Advantages	Dis –Advantages
Classical methods 1) L-Curve 2)GCV	Good Solutions for selecting Regularization Parameter.	
Bayesian Method	Lower computational load.	Not adaptive
U-Curve Method	Reduced computational load and is fully adaptive.	Adaptive

Fig.2 Regularization Parameter Selection Methods

to get the very high resolution. The following Fig 1 shows a table in which varies methods which solves the super resolution problem are mentioned it can be seen that frequency domain methods have the advantages of multi-frame resolution, removing spatial blur, and also reduces registration problems, while by using spatial domain methods we can incorporate the prior information about images which is difficult in case of frequency domain methods. Fig 2 shows the table of regularization parameter selection methods here classical methods have advantage of good solutions for selecting regularization parameter Bayesian Method have advantage of Lower computational load but it is not adaptive method last U-curve method reducescomputational load and is fully adaptive. Following table shows the comparative analysisof all the domainswhich are used for super resolution its advantages and is disadvantages also the table describes the methods of regularization parameter selection it's advantages and is disadvantages. From the tables we can get the brief idea related to the selection of a particular method.

III. BICUBIC INTERPOLATION METHOD.

One of the commonly used techniques for image resolution enhancement is interpolation. Interpolation has been widely used in many image processing application. Here we use DWT for image super resolution.DWT decomposes an image into different subband images, namely low-low (LL), low- high (LH), high-low (HL), and high-high (HH).Super resolution technique uses discrete wavelet transform (DWT) to decompose a low resolution image into different subband images. Then the high frequency subband images are interpolated using bicubic interpolation. In parallel, the input image is also interpolated separately. Finally, the interpolated high-frequency subband images and interpolated input image are combined by using inverse discrete wavelet transform (IDWT) to achieve a high-resolution output image. The Wavelet provide frequency information, space localization as well as high frequency details in an image viz. the horizontal, vertical and diagonal detail. Multi resolution analysis in wavelet provides the information about high frequency details at different levels of decomposition.The functionality of DWT [13] is that the columns of the original image are passed through a high-pass and low-pass filter. Then the rows of the filtered image are passed through the high-pass and low-pass filter. After the wavelet decomposition has been completed, the image will be divided into four sub images which are the approximate (LL), horizontal (LH), vertical (HL) and diagonal (HH). In order to obtain the approximate coefficients (LL), the rows and columns are passed through the low-pass filter which resembles the original image, but at a smaller resolution. The horizontal coefficients (LH) are obtained by passing the rows through the low-pass filter and the columns through the high-pass filter which will emphasize the horizontal edges. The vertical coefficients (HL) obtained by passing the columns through the low-pass filter and the rows through the high-pass filter that will stress the vertical edges. Lastly, when both the columns and rows are passed through the high-pass filter, this will produce the diagonal coefficients (HH) which accents the diagonal edges.In super resolution enhancement technique. The main loss of an image after being super resolved by applying interpolation is on its high-frequency components, that is, the edges. This loss is due to the smoothing caused by interpolation. Hence, in order to increase the quality of the super-resolved image, preserving the edges is essential. In this work DWT [14] has been employed in order to preserve the high-frequency components of the image

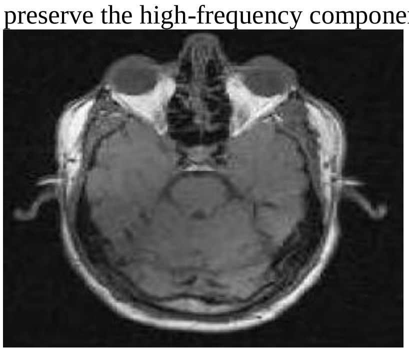


Fig.3(a)Original image.

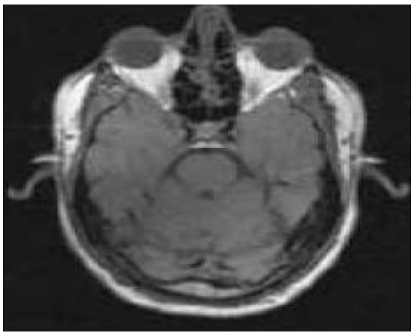


Fig.3 (b) Bicubic interpolated image [13]

In the wavelet domain, the LL subband image is the low-resolution of the original image. Therefore, instead of using LL, which contains less information, low resolution input image is used for interpolation. Hence, using low resolution input image instead of the LL subband image increases the quality of the super-resolved image [15]. Note that input image is interpolated with half of the interpolation factor α, used to interpolate the high frequency subbands By interpolating input image by α/2, and interpolating LH, HL, and HH by α, and then applying inverse discrete wavelet transform (IDWT), the output image will contain sharper edges than the interpolated image obtained by interpolation of the input image directly. This is because the interpolation of isolated high-frequency components in HH, HL, and LH will preserve more high-frequency components after the interpolation of the respective subbands separately than interpolating image directly.

Fig 4 Fig.(a) Fig.(b) Fig.(c) Fig.(d) [1]
a) Original Image b) Bi cubic interpolated image c) Super resolution image d) High Resolved Image.

IV. L-CURVE

Subsequent to the work of Kim, Bose, and Valenzuela in 1990on the simultaneous filtering and interpolation of a registered sequenceof undersampled noisy and shift-invariant blur degradedimages, Bose and Boo tackled in 1998 the problem of reconstructinga high-resolution image from multiple undersampled, shifted,degraded frames with subpixel displacement errors. This led toa formulation involving a periodically shift-variant system model.Lertrattanapanich and Bose advanced in 1999 a procedure for constructionof a high-resolution video mosaic following the estimationof motion parameters between successive frames in a videosequence generated from a video camera.When one solves an over determined system of linear equationsAx = b by minimizing $\|Ax-b\|2$ a discrete ill-posed problemsmay result if the matrix A is ill conditioned. The Tikhonovregularization procedureoffers a possible remedy for this problem.The Tikhonov regularized solution X_λ is defined as the solution of $\frac{min}{2}\{\|Ax-b\|_2^{2+\lambda}\|Lx\|_2^2$.Where λ is thedesired regularization parameter at the corner of the L-curve.

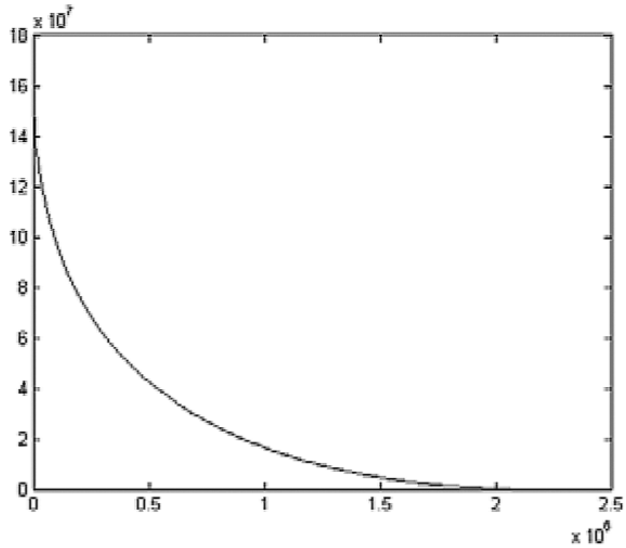


Fig.5 L-Curve

The algorithm for locating theλ at the corner of the L-curve issummarized next.

1. Start with a few points λ on each side of the corner
2. Estimate the three-dimensional cubic spline curve S from the points.
3. Let S2 denote the first two coordinates of S, i.e. S2 is an approximation to the L-curve.
4. Compute the point on S2 which gives themaximum curvature.
5. Add the new point to the L-curve.
6. Repeat from step 2

The optimal regularization parameter is calculated systematically using the L-curve methoddue to which we get high resolution images.[16]

V. MAP METHOD

1) MODEL UNDER OBSERVATION

Model under observation is the degradation process from an high resolution image to low resolution image.

Fig.6 Image Degradation model [1]

Here the original HR image is denoted in vector form by $x = [x_1\, x_2 \ldots x l_1 N_{1*}\, l_2 N_2]$ where$l_1 N_{1*}\, l_2 N_2$is the size of the HR image. Now, assume that the HR image is sub pixel shifted, blurred, down-sampled, and has some additive noise (Fig. 3), producing a sequence of LR images. Each frame of a sequence could be denoted in the vector form by $y_{k=[\,y_1 y_2 \ldots\ldots y N_1 * N_2]}$where$N_1 * N_2$ is the size of the LR image. $k = 1,2 \ldots\ldots k \ldots\ldots p$. The model under observation can be represented as,

$$y_k = D_k B_k M_k + n_k \qquad \ldots\ldots\ldots\ldots \quad (1)$$

Now, l_1 and l_2 be the down-sampled factors for rows and columns, respectively, M_k stands for the warp matrix with size $l_1 N_1 l_2 N_2 * l_1 N_1 l_2 N_2$, B_k is the blurring matrix (PSF) with $l_1 N_1 l_2 N_2 * l_1 N_1 l_2 N_2$, D_k is the down-sampling matrix with size $N_1 N_2 * l_1 N_1 l_2 N_2$, n_k is the noise vector with size MN.In this paper, we assume that the down-sample factors and blurring function remain the same between the LR images, so the matrices D_k and B_k will be substituted by matrices D, and respectively, in the remaining parts of the paper. Each LR image has an observation model in the form of equation (1). If we mix them, the whole observation model could be represented as,

$$y_1 = DBM_1 x + n_1$$

$$y_1 = DBM_2 x + n_2$$

:

:

$$y_1 = DBM_p x + n_p$$

Above equations can be combinely written as,

$$y_1 = DBMx + n \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (2)$$

Fig.4 Displacement parameter considering four low resolution images.

This is the model under observation now we will reconstruct this model by using MAP approach to get the equation for super resolution.

2) RECONSTRUCTION MODEL

By using MAP model we add some prior information about High resolution image to solve the super resolution problem.

1) MAP reconstruction model.

For obtained low resolution images above, the high resolution image can be given as,

$$\hat{x} = \arg max\{p(x/y)\} \qquad \ldots\ldots\ldots \quad (3)$$

By using Bayes rule above function can be written as,

$$\hat{x} = \arg max\{p(y/x)p(x)/p(y)\}\ldots\ldots\ldots\ldots \quad (4)$$

Above High resolution is independent of p(y) hence it can be written as,

$$\hat{x} = \arg max\left\{p(y_1 \ldots . y_p/x)p(x)\right\} \ \ldots\ldots\ldots \quad (5)$$

In above equation $p(y_1 \ldots . y_p/x)$ is possible distribution of low resolution image and p(x) is prior distribution of high resolution image.

The noise is considered as zero mean Gaussian noise hence of later obtained function, we minimize the minus log hence the equation becomes,

$$\hat{x} = \arg max\left\{-log\, p(y_1 \ldots . y_p/x) + log\, p(x)\right\} \ldots (6)$$

Considering Zero mean Gaussian noise and each low resolution frame independent the function $p(y_1 \ldots . y_p/x)$

Can be written as,

$$p(y_1 \ldots . y_p/x) = \left(\frac{1}{\sqrt{2\pi}\sigma k}\right)^p * \exp(-\sum_{k=1}^{p} IIy_k - DB_k M_k xII^2/2\sigma^2 k) \ldots\ldots\ldots\ldots\ldots \quad (7)$$

We are going to use following prior model in this paper

$$P(x) = 1/C \exp\{-1/nIIQxII^2\} \ \ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

In above equation n is parameter controlling variation in prior distribution and Q represents high pass operation for getting smooth result.

Putting equation (7) and (8) in equation (6) and solving it we get,

$$\hat{x} = \arg min\, J(x) = arg\ min\{IIy - DBM_x II^2 + \alpha IIQxII^2\} \ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

2) Optimization

To minimize the cost of the function we differentiate the above function with respect to x, and set result equal to zero we get,

$$\blacktriangledown J(x) = -2M^T B^T D^T (y - DBM_x) + 2\alpha Q^T Qx = 0. \ (10)$$

By using successive approximation iteration method we can solve high resolution image as,

$$x^{n+1} = x^n + \beta^n \gamma^n \qquad \ldots\ldots\ldots\ldots\ldots\ldots \ (11)$$

	Vertical pixel	Horizontal pixel
Image 1	0	0.5
Image 2	0	0
Image 3	0.5	0.5
Image 4	0.5	0

Fig.7 Subpixel Shifted Images.[1]

β^n Stands for nth iteration step size

The iteration is terminated when

$$IIx^{n+1} - x^n II2/IIx^n II2 \ \leq \text{d} \qquad \ldots\ldots\ldots\ldots\ldots \quad (12)$$

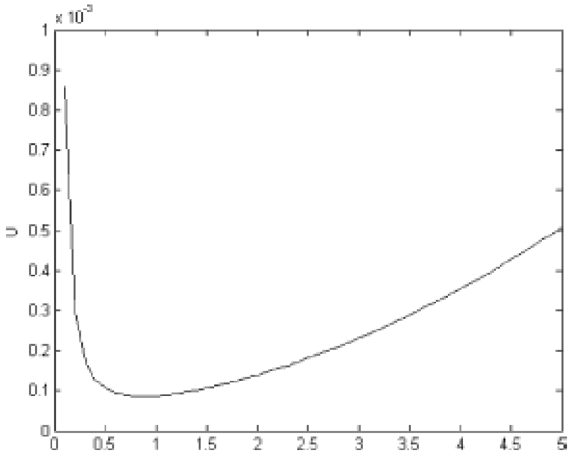
3). U-curve method and steps for selecting optimal regularization parameter.

By taking help of Tikhonov model , as our expressions will be same as it because we are considering Zero mean Gaussian noise, the U –curve can be plotted by using the function,

U(α)=1/R(α) + 1/p(α) ……………………. (13)

Where R(α) $= IIy - DBM_x II^2$ and p(α) = $IIQxII^2$

i.e. U- Curve is a plot of regularization parameter depending on data fidelity term and prior term as shown in Fig 5.



Regularization parameter

Fig. 8 U-Curve.[1]

Steps for selecting optimal regularization parameter

From Fig (5) we can have the observations as,

1) It is decreasing on the left side.

2) It is increasing on the right side.

3) And is almost horizontal at the middle.

In case 3 the data fidelity and prior term are close to each other. Hence we get high resolution when regularization parameter is in this area.

Now in this horizontal area we try number of values as regularization parameter value and try to incorporate the result.

VI. EXPERIMENTAL RESULTS.

a) b) c) d)
Fig9.a) original b) BI c) L-Curve d) U-Curve.[1]

	BI	L-Curve	U-Curve
MSE	490.525	194.098	149.995

Fig. 10 MSE values

images with the size of 128*28 is taken. The gray values of are between 0 and 255. In the case of known degradation parameters, the original HR image is shifted with sub pixel displacements to produce four LR images; the sequence is convoluted with Gaussian smooth filter PSF; then down-sampled in both the vertical and horizontal directions; lastly, zero-mean Gaussian-noise was added to the sequence. Here the motion matrix and blur matrix were both constructed with the known degradation parameters, results are compared with those of bilinear interpolation (BI), and the bi cubic interpolated (BCI), the adaptive iteration approach in and the L-curve method. The reconstruction factor was selected as 0.025. The MSE is employed to evaluate the gray value similarity is calculated.

Following are the results of paper and their respective table of comparison with other methods it can be clearly seen that results of U-curve are better as compared with other methods. The different images are the collection from internet database (google.com)

VII. CONCLUSION

By selecting the regularization parameter as 0.025 in the middle area of U-curve rather than considering the leftmost point as optimal regularization parameter we get the high resolution of the image, which produces smoothness in the obtained result and high quality output. In this paper, a U-curve method is utilized to select the Regularization parameter in the MAP SR reconstruction model. At start, the data fidelity and the prior model are used to construct a function for the regularization parameter. Then this function is plotted, which is the U-curve. Lastly, different values in middle area are chosen as optimal regularization parameter. Some advantages of our work are the following. First, an interval where the optimal regularization parameter exists is defined by the U-curve, which reduces calculations. Second, the U-curve method selects a more optimal regularization parameter than the L-curve, obtaining a better reconstruction result than the adaptive iteration method and L-curve method, and the reconstruction result is very good.

VIII. FUTURE SCOPE

The U-curve method based upon the Tikhonov regularization reconstruction model can be revised in some manner. As here we get a specific area for obtaining regularization parameter but for getting more accurate value we had tried number of possibilities rather than considering left most point of curvature as optimal parameter. In future work it could be focused on how to recover this and select a more accurate regularization parameter with some edge preserving prior models before using u-curve.

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