MULTI FRAME IMAGE SUPER RESOLUTION

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Abstract—**Super-resolution or reconstruction of an image is the strong requirement in current days. By using this technique we can obtain a high resolution image from several low resolution images which contains noise, or are blurred images. Numbers of reconstruction works are available out of which we are going to focus on MAP (Maximum a Posteriori) model. Regularization Parameter plays an important role in this model. If the parameter is too small or large then the reconstruction consists blur. Hence selecting the proper parameter gives High resolution output image.**

***Keyword*-MAP,Regularizationparameter,Bayesian framework, L-curve.**

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] **.**

The proposed paper is mainly based upon the MAP reconstruction model. The regularization parameter plays a very important role in this 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. 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.

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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 survey 2) Model for observation 3) Reconstruction Model 4) U curve method and Steps to select optimal regularization parameter. 5) Experimental results.

II. LITRETURE SURVEY

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 is a function 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 this parameter decides the amount of prior information which should added 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 reduces computational load and is fully adaptive. Following table shows the comparative analysis of all the domains which 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.

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Domain	Advantages	Dis – Advantages
Frequency Domain	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.	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

III.MODEL UNDER OBSERVATION

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

Fig.3 Image Degradation model

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 $y_{k=[\,y_1 y_2 \ldots y_{N_1 * N_2}]}$ where $N_1 * N_2$ is the size of the LR image. $k = 1,2 \ldots.. k \ldots.. p$. 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,

$$y_1 = DBM_1 x + n_1$$

$$y_1 = DBM_2 x + n_2$$

$$\vdots$$

$$y_1 = DBM_p x + n_p$$

Above equations can be combinely written as,

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

	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.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.

IV. 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,

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

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By using Bayes rule above function can be written as,

$\hat{x} = \arg max \{p(y/x)p(x)/p(y)\}$……….. (4)

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

$\hat{x} = \arg max \{p(y_1 \ldots . y_p/x)p(x)\}$ ……. (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,

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

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

We are going to use following prior model in this paper

P(x)=1/C exp$\{-1/nIIQxII^2\}$ ………………… (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,

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

1) 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,

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

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

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

β^n Stands for nth iteration step size.

The iteration is terminated when

$IIx^{n+1} - x^n II2/IIx^n II2$ ≤ d ……………… (12)

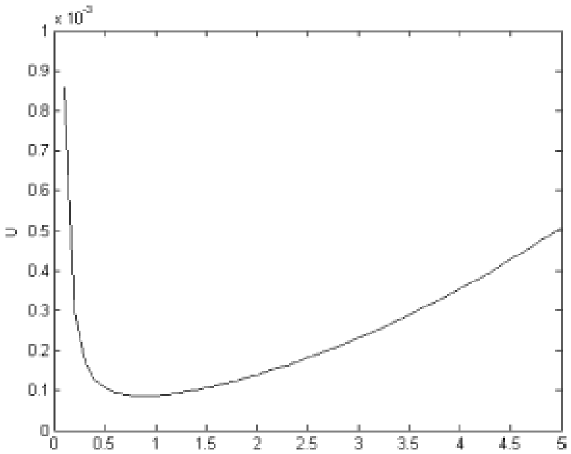
V. U-curve method and steps for selecting optimal regularization parameter.

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 5 U-Curve.

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.

The image consisting of four sub pixel displacement LR 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)

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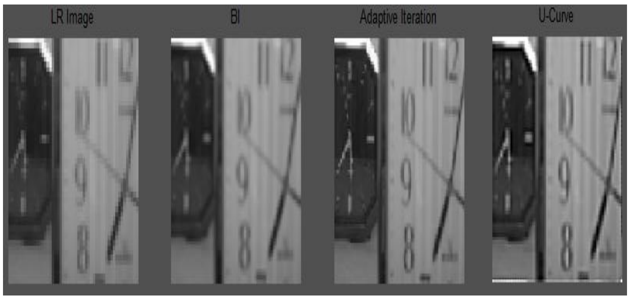

Fig 6 a) LR image b) BI c) Adaptive iteration d) U-curve.

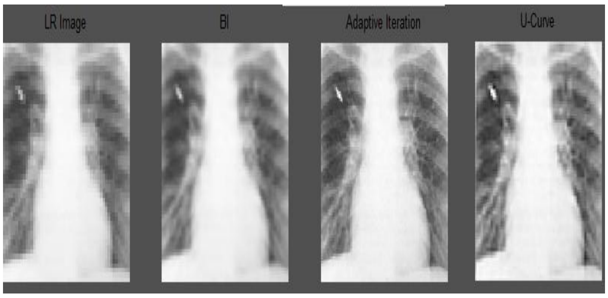

Fig 7 a) LR image b) BI c) Adaptive iteration d) U-curve.

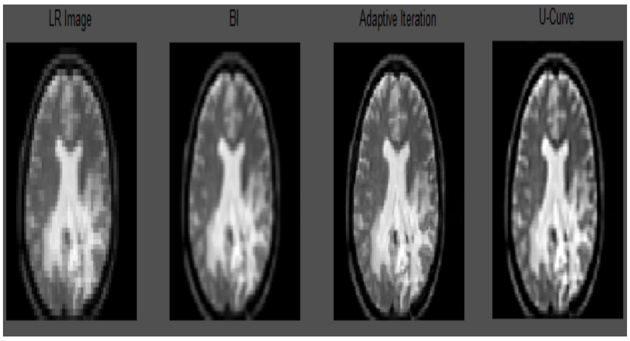

Fig 8 a) LR image b) BI c) Adaptive iteration d) U-curve.

For Fig.6

	U- CURVE
MSE	0.0416005

For Fig.7

	U- CURVE
MSE	0.0539274

For Fig.8

	U- CURVE
MSE	0.0808387

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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