Super Resolution Image Reconstruction Using Iterative Regularization Method and Feed–Forward Neural Networks

1M Ganesh Babu, 2Dr Sudam Sekhar Panda, 3Homer Benny Bandela

1Assistant Professor, Department of CSE, Sir C R Reddy College of Engineering, Eluru, India.
2Associate Professor, Department of MATHS, Vignan Foundation for Science Technology & Research, Guntur.
3Assistant Professor, Department of CSE, Sir C R Reddy College of Engineering, Eluru, India.
E-Mail: sudamshekhar@gmail.com

Abstract. Super resolution is one of the best existing procedures to acquire high resolution image due to its effortlessness and extensive variety of use in numerous fields of science and engineering. There are various methods exist for super resolution but, this work made an effort by combining the iterative regularization method with neural network and obtained a good result comparatively from the previous method because of its high compatible nature with less and user friendly approach. It takes care of the noise in the initial stage and gets a concrete result when neural network is introduced. In addition to the noise it controls the vulnerable parameters and gets a highly super resolution image as compare to the literature.

Index Terms: PSNR: Peak Signal to Noise Ratio, regularization, Neural networks.

1. Introduction
Regularization is often used to solve the problem of image restoration as an anti-existence of morbid or ill-posedness (ill-posed). The main purpose of regularization methods in super-resolution techniques is to get better recovery results by taking the image as a primary input. Regularization method to solve two important issues first is the regularization functional items to determine if Chiang Kai-shek, select regular item should be able to measure the signal of some kind of singularity, while at the same time be able to rebuild a better signal to maintain signal details. Followed by regularization coefficient of determination, choice of regularization factor should be able to ensure that the data fit according to the image information items and regular items of reasonable energy balance.
Regularization methods the main purpose is to introduce reasonable constraints to get better image restoration results. There are many improvements in regularization methods, like adaptive regularization parameter method, iterative regularization method, spatially adaptive wavelet method and regularization methods are seen in the literature but still the regularization image restoration process has its own significance in order to image smoothing and recovery. In 1960s Harris and Goodman proposed the single-image recovery concepts and methods [1], many of them subsequently conducted a study, and have proposed a variety of recovery methods. After this, taking into account the degraded image is a process of estimating the ill-posed problem, Schultz and Stevenson [2] made
a regularized motion estimation method, which will be used to estimate Bayesian motion block motion estimation, to obtain a satisfactory ultra-resolution reconstruction results. Hardie, Barnard and Bognar[3] also made an essentially identical with Schultz and Stevenson of the MAP method, the difference is that they take into account the overall and non-general motion model. Hardie was the promotion of this work, considering a motion estimation and super-resolution reconstruction problem solver simultaneously, and gives a great formula for a posteriori estimate. Although this formula converges more slowly, but because it is no longer the motion estimation parameters, like most other super-resolution reconstruction algorithm, as observed data to estimate the direct use of LR to get a better reconstruction results. Subsequently, Charbonnie and others worked on the basis of a new "half-quadratic regularization" method, where to get the optimal solution deterministic algorithm is used [4], while, Lagendijk, who proposed the weighted space restoration algorithm, MGKang and AKKatsaggelos the nonlinear regular iteration and regular iterative image restoration method is used by AKKatsaggelos and Jan Biemond [5]. In this paper, the appropriate selection of iterative regularization parameter has been done to stabilize the inversion of ill-posed problem and reconstructing an HR image with the help of neural network concept to overcome the effect of the noise. The result obtained has significantly shows the improvement in noise and texture reduction in HR image[9,10].

2. Image observation model

The observation model considered for the problem is written as

\[ Y_k = H_k X + N_k \quad 1 \leq k \leq p \] (2.1)

Where \( Y_k \) is the k frame image degradation, X For the high-resolution images to be restored. \( H_k \) is the Degradation of the k-frame matrix. \( p \) stands for the number of low-resolution images in the system.

The following model helps to determine the regularized parameter.

\[ \alpha = \arg \min \left\{ \| \gamma - \hat{H} \mathbf{x}(\alpha) \|^2 = \| \alpha \|^2 = MN\delta^2 \right\} \] (2.2)

Here \( \alpha \) is the regularization parameter and it is used to improve the recovery of the image which resolution is going to enhance by balancing the data items of the image. If the value of the is very small it cannot remove the high frequency noise effectively which leads to illusion and if the value of the \( \alpha \) is very large the image information will be missing. This concept helps the researchers to determine the value of the \( \alpha \) in an corrective manner. In this problem prediction mean square error method is used to find the regularized parameter incase of unknown noise variance.

\[ a_{\text{mse}} = \arg \min_{\alpha} \left\{ E \left( \| Hx - Hx(\alpha) \|^2 \right) \right\} \]

\[ = \arg \min_{\alpha} \left\{ \| (I - HR(\alpha))g \|^2 + 2\delta^2 \left( \text{tr} \left( HR(\alpha) \right) - MN \right) \right\} \] (2.3)

3. Neural Network - Proposed Training Algorithm Used In the Feed-Forward Back Propagation Algorithm

The main steps are as follows

1. Initialization of pixels to small random values(weight) and form a training set.
2. Select an ordered pair vector which consists of input and corresponding output.
3. Choose an input vector from the training set and treat as an input of the network.
4. In forward phase find and measure the actual outputs.
5. Find the difference between actual and desired outputs what we call it as error.
6. To reduce this error define an adjustment factor between \( W_d \) (desired weight) and \( W_a \) (actual weight).
7. Repeat step 4 to step-1 for all training vectors.
8. Repeat step 3 to step-1 till the error is significantly small.
4. Results and discussion

The original image and degraded image shown in Figure 4.1. Figure 4.2 shows respectively the global regularization and adaptive regularization method. The middle of the image shows that the global regularization method with adaptive regularization method compared better to keep the image edges and textures, while maintaining a better denoising effect. Reconstructed image shown in Figure 4.2, the calculation of the former PSNR = 50.282, whose PSNR = 52.465. As the adaptive regularization method based on image edges and smooth recovery to be the case for local self-adaptive control, got the better of the regular constraints and reconstruction effects. The PSNR value is calculated by taking the difference between the original image and reconstructed image. Moreover, when the PSNR value is large the quality of the reconstructed image is better.

\[
RMSE = \left( \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (f(i,j) - \hat{f}(i,j))^2 \right)^{1/2}
\]

\[
PSNR = 10 \log_{10} \left( \frac{M \times N}{RMSE^2} \right)
\]

Figure 4.1 (a) Original image, (b) regularized image

Figure 4.2 (a) is a global regularization method for image reconstruction, (b) adaptive regularization method for the reconstruction of image.

The image layer in the wavelet decomposition of sub-band has shown in Figure 4.3. As for the low frequency sub-bands LL, seen from the figure, which includes images of most of the edges and flat areas of information, and only a small number of high-frequency noise and information distributed in the HL, LH and HH sub-bands inside [6].
The change of noise discrete regularization parameter method with the wavelet decomposition, the weight \( m \) for different values of the reconstruction image has been shown in figure 4.3.

### Table 1

| Test image | Different values of \( m = W_d - W_a \) |
|------------|----------------------------------------|
|            | \( 10^{-1} \)  | \( 10^{-2} \)  | \( 10^{-3} \)  |
| PSNR       | 22.36       | 41.01       | 64.97         |

Tabl-1: shows the results of various image reconstructions PSNR. From the experimental results can be seen from the observation information to determine the regularization parameter, there is an optimal solution, so that the reconstruction process to get the best balance to get the best image super-resolution reconstruction results.

The local noise variance matrix interpolation algorithm used to get the same size as the original image of the new local noise variance matrix, the matrix element value is the degraded image in each pixel location is estimated noise variance. Resulting noise distribution is shown in Figure 4.4.

Figure 4.4, image quality has been reduced noise distribution

A noise variance estimate, then in accordance adaptive iterative calculation of regularization weights \( W(i, j) \), complete the iterative image reconstruction algorithm, the iterative process to pay attention to the repeated image of the new wavelet transform estimated noise. Finally, the results shown in Figure 4.5.
Figure 4.5 obtain the reconstructed image using training algorithm (Neural network)

The peak signal to noise ratio for the reconstructed image $\text{PSNR} = 55.39$, compared with the Adaptive regularization method, reconstruction results have improved significantly [10].

5. Conclusion

In order to better estimate the distribution of noise, it is clear that, wavelet decomposition in the high frequency sub-band noise can be good to extract the distribution of information, while the noise variance will be used in the regularization of adaptive parameters, to have a good image restoration results [7,8,9].

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