Compressed Sensing Image Recovery Using Adaptive Nonlinear Filtering

B. Sravanthi[1], Ch. Madhuri Devi[2]

[1]*M.tech.Student, Sri Indu College of Engineering & Technology, Hyderabad*

[2]*Associate Professor, Sri Indu College of Engineering & Technology, Hyderabad*

***Abstract**: Compressed sensing is a technique that consists providing efficient, stable and fast recovery algorithms which, in a few seconds, evaluate a good approximation of a compressible image from highly incomplete and noisy samples. In this paper, using adaptive nonlinear filtering strategies in an iterative framework can be avoiding the recovery image problem. In this technique has more efficient, stability and low computational cost. The experimental shows that the PSNR, CPU time and recovery image.*

***Index Terms**—Compressed sensing, L_1-minimization, median filters, nonlinear filters, sparse image recovery, total variation.*

I. Introdction

Compressed sensing is a new paradigm for signal recovery and sampling. It states that a relatively small number of linear measurements of a sparse signal can contain most of its salient information and that the signal can be exactly reconstructed from these highly incomplete observations. The major challenge in practical applications of compressed sensing consists in providing efficient, stable and fast recovery algorithms which, in a few seconds, evaluate a good approximation of a compressible image from highly incomplete and noisy samples.

It follows that signals that have a sparse representation in a transform domain can be exactly recovered from these measurements by solving an optimization problem of the form

$$\Phi W^T\alpha=\Phi X \qquad (1)$$

Here

Φ is an M*N measurement matrix and α=Wu. The number M of given measurements for which we obtain the perfect recovery depends upon the length and the sparsity level K of the original signal, and on the acquisition matrix [1], [3]. If the unknown x signal has sparse gradient, it has been shown in [2], [3] that it can be recovered by casting problem (1) as

$$\Phi u=\Phi x \qquad (2)$$

This formulation is particularly suited to the image recovery problem, since many images can be modeled as piece- wise-smooth functions containing a substantial number of jump discontinuities. Exact measurements are often not possible in real problems, so if the measurements are corrupted with random noise, namely we have

$$Y=\Phi x+e \qquad (3)$$

Where e is the error signal and x is the input image. Sparse signals are an idealization that we rarely encounter in applications, but real signals are quite often compressible with respect to an orthogonal basis. This means that, if expressed in that basis, their coefficients exhibit exponential decay when sorted by magnitude. As a consequence, compressible signals are well approximated by k-sparse signals and the compressed sensing paradigm guarantees that from M linear measurements we can obtain a reconstruction with an error comparable to that of the best possible k-terms approximation within the sparse fying basis [4][2].

In this paper is organized as follows. Proposed method in section II. Section III describes the comparative perfomance. The simulation results are presented in Section IV. Concluding remarks are made in Section V.

II. Proposed Method

In this paper, we consider an extension of this nonlinear filtering approach to the multi dimensional case. We focus on a recovery problem where the optimal solution, in addition to satisfying the acquisition constraints, has minimal “bounded variation norm,” namely, it minimizes. The optimal reconstruction is evaluated by solving a sequence of total variation regularized unconstrained sub problems, where both isotropic and anisotropic TV estimates have been considered.

The nonlinear filtering strategy has been proposed in the context of a penalized approach to the compressed sensing signal recovery problem. suitable filter is used according to the considered minimization problem and a fast flexible algorithm has been realized for its solution. The procedure of proposed method as shown below

i) Initialization of parameters
ii) Updating bound constrains
iii) Apply constraint non linear filter step
iv) Convergence test of proposed method
v) Updating outer iteration

From a theoretical point of view, the non linear adaptive filter is attractive since it can deal with a general class of nonlinear systems while its output is still linear with respect to various higher power system coefficients.

First we initialize the all parameter values then start with the outer iterations. In outer iteration, the image reconstruction problems it is well known that image intensity values have to be not negative and <=R,R>0. This suggests that we could insert more information in the compressed sensing reconstruction problem by adding a bound constraint as shown below

$$\mathbf{T_s u = y} \qquad (4)$$

In the case of input data perturbed by additive white Gaussian noise with standard deviation σ

$$\mathbf{Y=S(Tx+e)}$$
$$\mathbf{=Tsx+e_s} \qquad (5)$$

Where e error value between orginal image andreconstruction image. After apply the outer iteration then to update the bound constraints as shown below

$$v_{k,i} = u_{k,i} + \beta T_S^T (y - T_S u_{k,i}) \quad (6)$$

Where
Ts is linear operator
B < α/2
$V_{k,I}$ is the proximal operator argument
The third step of proposed method is the non linear filter step.The equation of non linear filter as shown below

$$u_{k,i+1} = \arg\min_{u \in C} \{1/2\lambda_{k,i}\beta \|u - v_{k,i}\|_2^2 + F(u)\} \quad (7)$$

The fourth step of proposed method is convergence test. In convergence test, The general compressed sensing problem can now be stated using the previous notations. The input data can be represented as

$$Y = T_s\, x \quad (8)$$

In the case of input data perturbed by additive white Gaussian noise with standard deviation σ in equation (5). If F(u) contains an L-norm the optimization problems can be very difficult to solve directly, due to the nondifferentiability of . To overcome this problem we use the well known penalization approach that considers a sequence of un-constrained minimization sub problems of the form

$$\min_{u \in R^{N_1 \times N_2}} \left\{ F(u) + \frac{1}{2\lambda_k} \|T_S u - y\|_2^2 \right\} \quad (9)$$

The convergence of the penalization method to the solution of the original constrained problem has been established (under very mild conditions) *lim λk =0* when. Unfortunately, in general, using very small penalization parameter values makes the unconstrained sub problems very ill-conditioned and difficult to solve. In the present context, we do not have this limitation, since we will approach these problems implicitly, thus, avoiding the need to deal with ill-conditioned linear systems. This is obtained by evaluating an approximation of the solution of (9) iteratively, using an operator splitting strategy (frequently considered in the literature to solve -regularized problems [5], [6], [7], [8]), and taking advantage of the particular structure of the resulting problems.

III. Comparative Perfomance

To assess the performance of the proposed filters for removal of noise and to evaluate their comparative performance, different standard performance indices have been used in the thesis. These are defined as follows:

Peak Signal to Noise Ratio (PSNR): It is measured in decibel (dB) and for gray scale image it is defined as:

$$\text{PSNR (dB)} = 10\log_{10}\left[\frac{\sum_i \sum_j 255^2}{\sum_i \sum_j \left(S_{i,j} - \hat{S}_{i,j}\right)^2}\right] \quad (8)$$

$S_{i,j}$ and $\hat{S}_{i,j}$ are the input and reconstruction images. The higher the PSNR in the restored image, the better is its quality.

Signal to Noise Ratio Improvement (SNRI): SNRI in dB is defined as the difference between the Signal to Noise Ratio (SNR) of the restored image in dB and SNR of restored image in dB i.e.

SNRI (dB) = SNR of restored image in dB- SNR of noisy image in dB
Where,
SNR of restored image dB=

$$10 \log_{10}\left[\frac{\sum_i \sum_j s_{i,j}^2}{\sum_i \sum_j \left(s_{i,j} - \hat{s}_{i,j}\right)^2}\right] \quad (9)$$

The higher value of SNRI reflects the better visual and restoration performance.

IV. EXPERIMENTAL RESULTS

Fig.1. original image

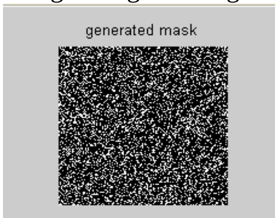

Fig.2. Gaussian mask corresponding to 77% under sampling

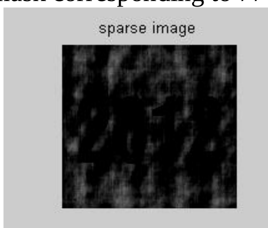

Fig.3. Sparse mask corresponding to 77% under sampling

Fig.4. reconstruction image using non linear filter

Nonlinear Adaptive Filter With Mask I,M=16402 with different noise

noise	PSNR	SNR	Cpu time	iteration
0	55.15	220	12	25
0.1	54.98	219	12	26

V. CONCLUSION

In this paper, avoiding the reconstruction image problem using non linear filter technique and prove the convergence of the resulting two-steps iterative scheme.In this paper, different kinds of measurements and different choices of the function F(u). In fact, since this function plays the role of the penalty function in the variational approach of the image denoising problem, it is possible to exploit the different proposals of the denoising literature in order to select new filtering strategies and the references therein), perhaps more suited to the different practical recovery problems.

References

[1] E. J. Candés, "Compressive sampling," in Proc. Int. Congr. Math., Madrid, Spain, 2006, vol. 3, pp. 1433–1452.

[2] E. J. Candés, J. Romberg, and T. Tao, "Stable signal recovery from in-complete and inaccurate measurements," Commun. Pure Appl. Math.,vol. 59, no. 8, pp. 1207–1223, 2006.

[3] E. J. Candés, J. Romberg, and T. Tao, "Robust uncertainty principle: Exact signal reconstruction fromhighly incomplete frequency information," IEEE Trans. Inf. Theory, vol. 52, no. 2, pp. 489–509, Feb. 2006.

[4] A. Chambolle, "An algorithm for total variation minimization and applications," J. Math. Imag. Vis., vol. 20, pp. 89–97, 2004.

[5] P. L. Combettes andV. R.Wajs, "Signal recovery by proximal forward-backward splitting," SIAM J. Multiscale Model. Sim., vol. 4, no. 4, pp. 1168–1200, Nov. 2005.

[6] I. Daubechies, M. Defrise, and C. De Mol, "An iterative thresholding algorithm for linear inverse problems with a sparsity constraint,"Commun. Pure Appl. Math., vol. LVII, pp. 1413–1457, 2004.

[7] T. Goldstein and S. Osher, "The split Bregman algorithm for L1 regularized problems," UCLA, Los Angeles, CA, UCLA CAMRep. 08–29,2008.

[8] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," Phys. D, vol. 60, pp. 259–268, 1992.

Miss. **BEJAWADA SRAVANTHI** graduate from The vazeer sulthan colg of Engg College in **Electronics& Communications**. Now pursuing Masters in **Digital Electronics and Communication Systems** (DECS) from Sri Indu College of Engineering & Technology.

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