An Innovative Quasi Newton Method for Enhancing Ultrasound Medical Image Quality

Deepa Parasar
Assistant Professor, SCOE,Kharghar

Dr. Vijay R. Rathod
Professor, XIT,Mahim

Abstract- **The aim of this paper is to introduce a novel variational method for enhancement of quality of ultrasound image. Medical imaging provides an effective and non-invasive mapping of the anatomy of human body. Pathological conditions of body tissues produce different image patterns and the patterns exhibited by the biological tissues through their images have been in routine clinical use for medical diagnosis purposes. Medical image understanding is a computing process of object recognition in medical image using computer vision, applied mathematics, signal analysis and artificial intelligence Image processing is the use of computer algorithms to perform image processing on digital images. Quasi-Newton (QN) based iteration of the proposed algorithm helps in converging towards a saddle point with locally isotropic convergence. This convergence is regardless of the spatial and spectral distributions of medical images. Hence, this proposed QN – UICA (Unbiased Independent Component Analysis) gives major contribution in the classification of medical images. The experimental results show that the proposed QN-UICA has better classification accuracy and convergence rate to resolve the problems of mixed classes in the medical image classification.**

Keywords-**Median Filter, Fuzzy C-Means Segmentation, Quasi-Newton, Ultrasound Images.**

I. INTRODUCTION

Medical Imageology is a cross-discipline to study imaging technology of biomedicine. And it is an important part of iatrology diagnosis technology. Pathological conditions of body tissues produce different image patterns and the patterns exhibited by the biological tissues through their images have been in routine clinical use for medical diagnosis purposes [1]. In iatrology, the image has very significant sense for people understanding disease. Medical image understanding is a computing process of object recognition in medical image using computer vision, applied mathematics, signal analysis and artificial intelligence Image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analog image processing; it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing [2-3]. Image analysis usually refers to processing of images by computer with the goal of finding what objects are presented in the image. Image segmentation is one of the most critical tasks in automatic image analysis. Over the years, the research in the medical imaging has produced many different imaging modalities for the clinical purpose. The different imaging technologies provide the exceptional views of the internal anatomy and the trained radiologist quantify and analyze the embedded structures. The most common imaging modalities are X-rays, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound etc. Among the medical images from different imaging modalities, ultrasound B-scan images are widely used. This widespread choice is due to its cost effectiveness, portability, acceptability and safety. The choice of the best imaging modality, to either help or to solve any particular clinical problem, is based on the factors such as resolution, contrast mechanism, speed, convenience, acceptability and safety [4]. The cost effectiveness and portability of the modality is particularly important in countries like India to allow widespread access or to provide sophisticated medical imaging. Due to its ability to visualize human tissue without deleterious effect, ultrasound B-scan imaging has become the most widely used technique for imaging soft tissues such as the lungs, liver, prostate, uterus, spleen, kidney and bone fracture etc. Medical ultrasound images which are obtained from coherent energy, often suffer from the interference of backscattered echoes from the randomly distributed scatters, called speckle [5]. Speckle is considered as a multiplicative noise that obscures the fine details in the images such as lesions with faint grey value transitions and small details. Due to presence of the high level noise (speckle), the quality of the ultrasound image degrades. It is very much essential to develop efficient denoising techniques which are used to suppress the noise in an image and to preserve the edges and fine details of the original image in the restored image as much as possible [6]. Jacques Demongeot [7] proposed a collection of analytic methods for solving tasks of low level image processing like contrasting, segmenting and contouring. A.P.H. Butler et al. [8] studied to review the clinical potential of spectroscopic X-ray detectors and to undertake a feasibility study using a novel detector in a clinical hospital setting. Hence, proposed QN-UICA quite adaptable and extendable algorithm for a user to separate the different classes. At the moment of source separation, the gradient of $\psi(G)$ disappears suddenly (at the expression of G = I or any permutation matrix). The gradient of $\psi(G)$ with respect to G is obtained by using the cumulants properties as follows,

$$\frac{\partial \psi(G_r)}{\partial G_r} = S_x{}^{\beta} C_{x,s}^{\beta,1} - G^{-T} \quad \textbf{(1)}$$

When the gradient is equating to zero than the estimating equation is significantly denoted as,

$$S_x{}^{\beta} C_{x,x}^{\beta,1} = I \quad \textbf{(2)}$$

the above equation depends only on the outputs and its solution will go ahead to an equivalent approximate of matrix G [9].

II. PROPOSED WORK

A. *Quasi Newton Algorithm*

In this section, an algorithm is explained that help to converge towards the disjoint solution. Since source partition is not at least or utmost of $\psi(G)$ but a saddle point, gradient-based approaches cannot be utilized as the predictable gradient or the innate gradient [9, 11] to adapt the segregation system. Instead, the BSS solution is suggested by using a preconditioned process, which uses the second-order information existing at partition. In order to get the zeros of the gradient, the exploitation of a preconditioned iteration [11] of the form is recommended as

$$vecG_r{}^{(m+1)} = vecG_r{}^{(m)} - \mu^{(m)} (\hat{h}\psi)^{-1} vec(\frac{\partial \psi}{\partial G_r}) \quad \textbf{(3)}$$

Where $\hat{h}\psi$ is defined as an estimation of the true Hessian matrix in the region of the partition. This category of numerical algorithm is an alternate of the quasi-Newton chord methods [9]. This Hessian approximation is proposed as follows,

$$\hat{h}\psi(G_r) = k_M((G_r{}^{-1})^T \otimes G_r{}^{-1}), \quad \textbf{(4)}$$

It shows the difference only in the diagonal terms of the true Hessian matrix. Furthermore, on the separation of the classes, the aforesaid difference will become negligible, due to the Hessian approximation. It keeps true hessian for the Eigenvalues with a single module. On the other hand, as the Eq. (1) shows this difference is an important as the deceptive results of the estimating Eq. (2). For these, the true hessian plays an important role to change the sign of some Eigenvalues of the Hessian approximation in their respective, to avoid the possibility of converging towards non-separating solutions. On Substituting (4) into the iteration (3) and then the following expression in the following algorithm:

$$G_r{}^{(m+1)} = G_r{}^{(m)} - \mu^{(m)} (C_{x,x}^{1,\beta} S_x^{\beta} - I) G_r{}^{(m)}, \quad \textbf{(5)}$$

The term A^{-1} is multiplied in the right part of Eq. (5), then the separating system is obtained as in the following Eq. (6),

$$B_s{}^{(m+1)} = B_s{}^{(m)} - \mu^{(m)} (C_{x,x}^{1,\beta} S_x^{\beta} - I) B_s{}^{(m)}, \quad \textbf{(6)}$$

This expression denoted as the CII (cumulant-based iterative inversion) term which is significantly also known as Quasi-Newton method, due to the recursion property. This method inverts the system iteratively in a very robust manner to estimate the mixing system, which is estimated as $\hat{A}(B_s{}^{(m)}) = C_{y,x}^{1,\beta} S_x^{\beta}$ (see [12, 13] for further details). By the way, it is an expected observation to find out the following recursion expression, in the CII algorithm at set β = 1,

$$B_s{}^{(m+1)} = (I - \mu^{(m)} (C_{x,x}^{1,1} - I)) B_s{}^{(m)} \quad \textbf{(7)}$$

It searches the diagonalization of the symmetric correlation matrix $C_{x,x}^{1,1}$. Almeida et al. proposed a globally stable decorrelation algorithm [14]. The algorithm CII considers $Sym_{cr}{}^{\beta} = diag(sign(diag(C_{x,x}^{1,\beta})))$ for implementation and the moments of the outputs are used to find the cumulant matrix $C_{x,x}^{1,\beta}$. The following given component matrix, considers as for real signal on the value of $\beta = 3$,

$$B_s^{(m+1)} = B_s^{(m)} - \mu^{(m)}.\Big((E[x(x^{\odot 3})^T] - 3E[xx^T]diag(E[x^{\odot 2}])\Big) S_x^3 - I) B_s^{(m)} \quad (8)$$

Where the diagonal elements are defined as $[S_x{}^3]_{ii} = sign(E[x_i^4] - 3(E[x_i^2]^2)$ in the matrix $S_x{}^3$.

The overall observation significantly shows the possibility of an adaptation of similar kind of structural form such as Natural Gradient [9, 11] in the CII algorithms having the stochastic versions. Only keeping the exception of the positional interchanging between linear and non-linear functions such as,

$$B_s{}^{(m+1)} = B_s{}^{(m)} - \mu^{(m)} (yg(y)^T - I) B_s{}^{(m)}, \quad \textbf{(9)}$$

Where $g(.)$ is the appropriate function that behaves as component wise of the output vector.

$[g(x)]_i = (x_i^3 - 3x_i\hat{\sigma}_{x_i}^2)\hat{S}_{x_i}^3$ is found for the case of $\beta = 3$ order value, where $\hat{\sigma}_{x_i}^2$ and $\hat{S}_{x_i}^3$ are expresses as the adaptive estimates i[th] output power and of the sign of its fourth-order cumulant respectively.

1) *Optimal selection of the step-size*

Due to the nature of quasi-Newton type, the CII algorithm confirmed the mechanism region limitation always in the continuous fashion on $\Psi(G_r)$. Even on the singularity property of the matrix B, the region will not cross or reach the discontinuities. To ensure that $\|\Delta^{(m)}\|<1$, which is an essential condition for $B_s^{(m+1)}=(I-\Delta^{(m)})B_s^{(m)}$ to be singular is that $\|\Delta^{(m)}\|\geq 1$ for any chosen matrix norm. Since the triangular inequality is considered as,

$$\left\|C_{x,x}^{1,\beta}S_x^{\beta}-I\right\|\leq 1+\left\|C_{x,x}^{1,\beta}S_x^{\beta}\right\|=1+\left\|C_{x,x}^{1,\beta}\right\| \quad \textbf{(10)}$$

It is an adequate expression to prefer,

$$\mu^{(m)}=\min\left(\frac{2\eta}{1+\eta\beta},\frac{\eta}{1+\eta\left\|C_{x,x}^{1,\beta}\right\|}\right) \quad \textbf{(11)}$$

Here the $\eta<1$ and the term $2\eta/(1+\eta\beta)$ should consider as the convergence properties of the algorithm to avoid $B_s^{(m+1)}$ becoming singular.

2) To incorporate additional information of higher order

One of the major problem occurs in the CII algorithm, due to the zero value of the $C_s^{1+\beta}$ cumulant for any of the sources. A set of indexes has to be incorporated $\Omega=\{\beta_1,.....,\beta_{N\Omega}:\beta_i\in N^+,\beta_i\neq 1\}$ to resolve this drawback. It will resolve in such a way that No one sources removes by the sum of cumulants $\sum_{\beta\in\Omega}\left|C_{s_i}^{1+\beta}\right|$. The non-Gaussianity of the sources proves the existence of at least one possible set Ω. A weighted sum of many cumulants as the resulted outcomes whose index β related to the set Ω, is used to measure the non-gaussianity in place of a single cumulant,

$$h(x_i)\rightarrow\sum_{\beta\in\Omega}w_\beta\frac{\left|C_{x_i}^{1+\beta}\right|}{1+\beta}, \quad \textbf{(12)}$$

To achieve the $\sum_{\beta\in\Omega}w_\beta=1$, a weighting terms w_β chooses as positive. The second-order information is not included from this weighted sum at the condition of $1\notin\Omega$. On considering the similar steps of aforesaid, a saddle point signifies the disjoint sets in the ensuing. In the similar way, the saddle point can be found by the results of the comprehensive and cumulant-based iterative inversion (GCII) algorithm,

$$B_s^{(m+1)}=B_s^{(m)}-\mu^{(m)}\left(\sum_{\beta\in\Omega}w_\beta C_{x,x}^{1+\beta}S_x^{\beta}-I\right)B_s^{(m)}, \quad \textbf{(13)}$$

Where,

$$\mu^{(m)}=\min\left\{\frac{2\eta}{1+\eta\sum_{\beta\in\Omega}w_\beta\beta},\frac{\eta}{1+\eta\left\|\sum_{\beta\in\Omega}w_\beta C_{x,x}^{1,\beta}S_x^{\beta}\right\|}\right\} \quad (14)$$

with $\eta<1$ and $\sum_{\beta\in\Omega}w_\beta=1$

Therefore, the advanced version of the algorithm utilizes many cumulants matrices to make it extra robust in the sense of deducting the probability which emphasizes mainly on a specific cumulant. These deductions come due to the occurrence of a few bad choices of cumulant sequence whose outcomes in near zero values of the weighted sum of cumulants for few sources. Additionally, the statistical information utilizes in best way by using many cumulants matrices in the proposed algorithm. However, the variance of the cumulant estimation is inversely proportional to the selected weighting factor. Some applications related to color and non-stationary source based information can also consider as the extension of the additional algorithms. It can be achieved by replacing the self-cumulants $C_{x_i}^{1+\beta}$ accompany with cross-cumulants in the structure of $Cum(y_i[m],y_i[m-t_1],......,y_i[m-t_d])$ where $t_d, d=1,....,\beta,$ are properly selected time delays which satisfy $\sum_{\beta\in\Omega}Cum(s_i[m],s_i[m-t_1],......,s_i[m-t_d])\neq 0\forall i.$ In this scenario, the defined form of the algorithm is quite similar as aforesaid algorithm, except for the details, which defines the information of cross-cumulant matrices in such a way $C_{x_i,x_j}^{1,\beta}=Cum(y_i[m],y_i[m-t_1],......,y_i[m-t_d])$.

III. Flow Diagram

The following flow diagram based on Quasi-Newton method has been used for enhancing the quality of ultrasound medical image.

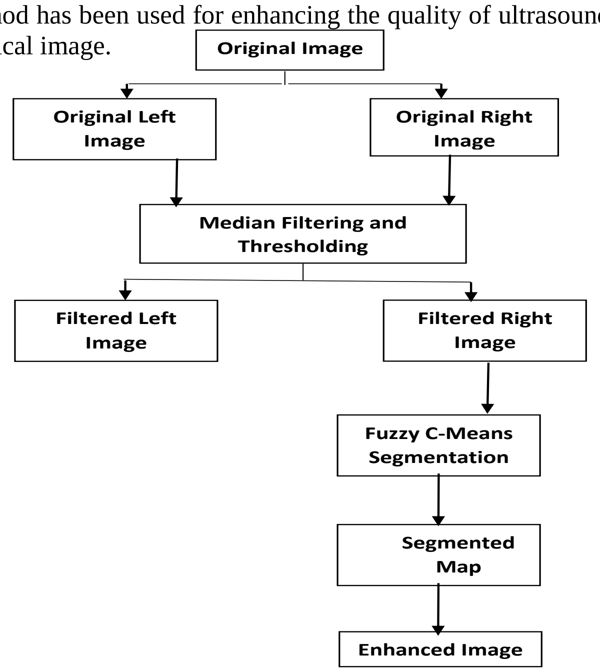

Fig.1. flow chart

IV. RESULTS AND DISCUSSIONS

The results for proposed QN-UICA approach on ultrasound images are shown below.

Fig 1 shows the ultrasound image of a fetus of 16.7 cm.

Fig.1. Original Ultrasound Input Image

Fig 2 is the enhanced image of the fetus after applying QN-UICA method on input image. By viewing Fig 1 and Fig 2 it is been clear that it is to recognize and analyze the area of interest after enhancement of image.

Fig.2. Enhanced Image

Fig 3 and Fig 4 are left and right image of the input image. For the dataset of Ultrasound images it is not possible to have the left and right image but the proposed method uses the concept of left and right image so we have used the same input image as left image and right image.

Fig.3. Left Image of Input Image

Fig.4. Right Image of Input Image

Median Filters are applied on the left image and right image of input ultrasound image. Median Filters can do excellent job of rejecting noise, in particular, “shot” or impulse noise in which some individual pixels have extreme values. It has been shown in Fig 5 and Fig 6. Default Thresholding value i.e half of size of image is considered here for finding out Left Filtered Threshold image and Right Filtered Threshold image as being shown in Fig 7 and Fig. 8.

Fig.5. Left Filtered Image of Input Image

Fig.6. Right Filtered Image of Input Image

Fig.7. Left Filtered Threshold Image

Fig.8. Right Filtered Threshold Image

Fuzzy C-Means segmentation assigns pixels to clusters based on their fuzzy membership values. Fuzzy membership values are assigned to pixels based on their distance from the center of different clusters. The smaller the distance of pixel under consideration from cluster centroid, higher will be the degree of membership to that cluster and vice-versa. The Fuzzy C-mean segmented image is shown in Fig 9.

Fig.9. Fuzzy C-Mean Segmented Image

Statistical analysis of the Input Image and the Enhanced Image is as shown in following table.

Absolute Difference	61.0247
Signal to noise ratio	1.1615
Peak signal to noise ratio	11.1330
Image fidelity	-0.7653
Mean squared Error	5.0093e+03
Root Mean squared Error	70.7765

V. CONCLUSION

In this paper we have improved the quality of ultrasound image by using median filter and Fuzzy C-means segmentation to remove noises by preserving edges and thresholding is done on them. Results provided by median filter are able to remove noise, reduce speckles, preserve edges and can be used in real time application. The obtained results demonstrate that the proposed Quasi Newton method increases the medical image quality as we have seen Fig 2 the areas which are of interest are getting more highlighted.

REFERENCES

[1] A.P. Dhawan, *Medical Image Analysis*.: John Wiley Publication and IEEE Press, 2003
[2] Mora B, Maciejewski R, Chen M, et al, "Visualization and computer graphics on isotropically emissive volumetric displays" , IEEE on visualization and computer graphics, 2009; 15(2): 221-233.
[3] Draper BA, Beveridge JR, "Teaching image computation: From computer graphics to computer vision" , International journal of pattern recognition and artificial intelligence, 2001; 15(5): 823-831.
[4] P.N.T. Wells, "Current status and future technical advances of ultrasonic imaging," *IEEE Engineering in Medicine and Biology Magazine*, vol. 19, no. 5, pp. 14-20, 2000.
[5] C.B. Burckhardt, "Speckle in ultrasound B-mode scans," *IEEE Transaction on Sonics and Ultrasonics*, vol. SU-25, no. 1, pp. 1-6, 1978
[6] R. Touzi, "A review of speckle filtering in the context of estimation theory," *IEEE Transaction on Geosciences and Remote Sensing*, vol. 40, pp. 2392-2404, 2002.
[7] Jacques Demongeot "A brief history about analytic tools in medical imaging: splines, wavelets, singularities and partial differential equations", Proceedings of the 29th Annual International Conference of the IEEE EMBS Cité Internationale, Lyon, France August 23-26, 2007.
[8] A.P.H. Butler, N.G. Anderson, R. Tipples, N. Cook, R. Watts, J. Meyerf, A.J. Bell, T.R. Melzer, P.H. Butler "Bio-medical X-ray imaging with spectroscopic pixel detectors", Nuclear Instruments and Methods in Physics Research A 591 (2008) 141–146
[9] S. Cruces, L. Castedo, and A. Cichocki, "Robust blind source separation algorithms using cumulants," *Neuro computing*, vol. 49, no.1-4, pp. 87-118, 2002.
[10] S. Cruces, A. Cichocki, and L. Castedo, "An iterative inversion approach to blind source separation," *IEEE Trans. Neural Networks*, vol. 11, no. 6, pp. 1423–1437, 2000.
[11] L. Zhang, A. Cichocki, and S. Amari, "Natural Gradient Algorithm to Blind Separation of Over determined Mixture with Additive Noises," *IEEE Signal Processing Letters*, vol. 6, no. 11, pp. 293-295, 1999.
[12] C.T. Kelley, "Iterative methods for linear and nonlinear equations," *In: Frontiers in Applied Mathematics*, SIAM, Philadelphia, PA, vol. 16, 1995, pp. 71–78.
[13] L. Zhang, S. Amari, and A. Cichocki, "Natural Gradient Approach to Blind Separation of Over- and Under-complete Mixtures," *In Proceedings of ICA'99*, Aussois, France, 1999, pp. 455-460.
[14] S. Cruces, L. Castedo, and A. Cichocki, "Novel Blind Source Separation Algorithms Using Cumulants," *In IEEE International Conference on Acoustics, Speech, and Signal Processing*, Vol. V, Istanbul, Turkey, pp. 3152-3155, 2000.