A Comparative Performance Evaluation of Independent Component Analysis in Medical Image Denoising

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***Abstract*— Medical images are often corrupted by noise arising in image acquisition process. Accurate diagnosis of the disease requires that medical images be sharp, clear and free of noise. Thus, image denoising is one of the fundamental tasks required by medical image analysis. There exist several denoising techniques for medical images like Median, Wavelet, Wiener, Average and Independent component analysis (ICA) filters. The independent component analysis is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. In this paper, ICA has been used to separate out noise from the image to provide important diagnostic information to the physician and its usefulness is demonstrated by comparing its performance with other noise filtering methods. The performance of the ICA and other denoising techniques is evaluated using the metrics like Peak Signal-to-Noise Ratio (PSNR), Mean Absolute Error (MAE) and Mean Structural Similarity Index (MSSIM). The ICA based noise filtering technique gives 25.8245 dB of PSNR, 0.7312 of MAE and 0.9120 of SSIM. The experimental results and the performance comparisons show that ICA proves to be the effective method in eliminating noise from the medical image.**

***Keywords*—Independent component analysis, Medical image, Denoise, Statistical independence, Negentropy.**

I. INTRODUCTION

The advent of medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and X-ray has revolutionized modern medicine [1]. Some of the diseases of the organs like cancer require early diagnosis in order to reduce the death rate. The medical imaging techniques play vital role in providing important information about the organ to the physician in a non invasive manner and help in detecting the disease as early as possible.

With the wide spread use of digital imaging in medicine today, the quality of the digital images becomes an important issue. Medical images are usually corrupted by noise. The noise can mask and blur important features in the image and thus make the further steps in image analysis more difficult [2]. Hence to achieve the best possible diagnosis it is important that medical images be free of noise and thus preprocessing is one of the important task in medical image processing.

Independent component analysis is an emerging technique in signal processing and machine learning which has received more attention in fields like image processing, speech processing and biomedical signal processing [3]. ICA decomposes random vector into linear components which are statistically independent and nongaussian. In this paper, ICA has been used to separate out noise from the image in order to improve the quality of the image. Numerous de-noising approaches have been proposed in the literature, such as Wavelets, Wiener [8], Median and Average filtering [9]. All these methods consider the signal and noise as the same status but not consider the independence of signal and noise, so they may tend to affect the denoising effect. And in these algorithms denoising is achieved by averaging and using low-pass filtering. The noise is captured by the high frequency coefficients, thus by filtering these coefficients, the unwanted noise is removed. Unfortunately, edges also have high frequency components and by removing the noise, high frequency components belonging to edges are also removed [5]. The advantage of ICA based filtering compared to other filtering methods is that it renders the images as statistically independent as possible by evaluating higher-order statistics of observation images. Hence it performs well in noise removal. The ICA also preserves edge sharpness while denoising the image and thus retains the important information in the image. In this paper, a comparative study on performance of ICA has been made with other existing denoising techniques.

II. ICA MODEL

ICA is a method of blind source separation which extracts the original signals from their mixtures without having any prior knowledge about the signals or the mixing process [3]. ICA model can be defined as:

$$X(t) = AS(t) + N(t) \tag{1}$$

Where $X(t) = [\, x_1(t), x_2(t), \ldots, x_m(t)\,]^T$ is the observed random

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vector of size m-dimension at time *t*; $S(t) = [\ s_1(t),\ s_2\ (t),\ \ldots,\ s_n(t)\ ]^T$ is the latent *n*-dimensional random vector at time *t*; A is a constant $m\times n$ mixing matrix; $N(t) = [\ n_1(t),\ n_2(t),\ \ldots,\ n_m(t)\ ]^T$ is a *m*-dimensional random noise vector and it is white, gaussian and statistically independent. The ICA problem is to estimate the latent variable *S(t)* in terms of the observed variable *X(t)* without any information about the matrix *A*. The estimation is performed by formulating an objective function and then minimizing or maximizing it. There are some objective functions developed in recent years, such as maximum likelihood estimation, maximization of nongaussianity, minimization of mutual information and so on.

III. ICA ALGORITHM

There exist some ICA algorithms such as maximum likelihood estimation algorithm [4], Non-linear PCA algorithm [6], the FastICA algorithm [7], and so on. In this paper, the FastICA algorithm based on negentropy is used to perform independent component analysis to denoise the image. The negentropy is differential entropy which acts as a measure of nonguassianity. In the course of independent component estimation we must have a quantitative measure of nongaussianity to observe the independence of the results. When the measure of nongaussianity attains maximum value, it shows that estimation has been completed.

A. ICA by Maximization of Nongaussianity

In this method, the FastICA algorithm based on negentropy estimates the latent variables based on maximization of nongaussianity. The central limit theorem states that the distribution of a sum of independent random variables tends towards a gaussian distribution, under certain conditions. Estimating the independent components can be accomplished by finding the right linear combinations of the mixture variables, since we can invert the mixing as

$$S = A^{-1} X \tag{2}$$

Thus to estimate one of the independent components, we can consider a linear combination of x_i. Let us denote this by

$$Y = b^T X = b^T AS \tag{3}$$

Hence if b were one of the rows of A^{-1}, this linear combination $b^T X$ would actually equal one of the independent components. The FastICA algorithm includes two pre-processing steps, cantering and whitening. The vector *X* is centered by subtracting its mean. Then whitening is performed by eigen value decomposition of the covariance of *X*. The whitening makes underlying components uncorrelated but cannot separate them from each other. After pre-processing stage components are uncorrelated and have unit variance. The complete steps of the FastICA algorithm are given as follows:

1. Center the data to make its mean zero.
2. Whiten the data to give Z.
3. Choose an initial vector W of unit norm.
4. Let $W = E\{Zg(W^TZ)\} - E\{g'(W^TZ)\}W$.

   Where g is defined as,

   g(y)= tanh(y) or

   g(y)= y3
5. Orthogonalize the matrix W.
6. Make W=W/norm(W)
7. If not converged, go back to step 4.

Here convergence means that the old and new values of W point in the same direction. That is, the absolute value of their dot product is almost equal to 1. The ICA algorithm has been widely used in multiple channel denoising. It removes the noise that is mixed with the original image before reaching the imaging device. The noise in this case can be formulated as:

$$X=AS+N \tag{4}$$

If the noise is added to the image after the image is received by the sensor or the device, then the traditional ICA algorithm cannot denoise the image. In this case the noise has to be estimated from the image and then it should be cancelled out from the image. The noise in this case can be formulated as:

$$X=A(S+N) \tag{5}$$

The processing of noise estimation is depicted as follows:

(1) Estimate the mean and variance of the noise block image around each pixel. The mean and variance are estimated by the following equations .

$$\mu = \frac{1}{NM}\sum_{x=1}^{N}\sum_{y=1}^{M} t(x,y) \tag{6}$$

$$\sigma^2 = \sum_{x=1}^{N}\sum_{y=1}^{M}(t^2(x,y)) - \mu^2) \tag{7}$$

Where $M\times N$ is the *N*-by-*M* local neighbourhood of each pixel in the image.

(2) Estimate the noise in the image.

$$\hat{n}(x,y) = \frac{v^2}{\sigma^2}(t(x,y) - \mu) \tag{8}$$

Where v^2 is the noise variance which is taken as the average of all the local estimated variances.

IV. Results and Discussion

The experiment was performed by applying FastICA algorithm and the noise estimation on several noisy images. The code was written and simulated in MATLAB 7.0. The size of each image is 256 × 256. All the images are in gray scale. To demonstrate the performance of the ICA based denoising technique, its results are compared with the other denoising methods like wavelet, median, averaging and wiener filter.

The Fig. 1 and Fig. 2 shows the original noise free image and noisy medical MRI image of the head respectively. The noise in the image has obscured the details in the image. The Fig. 3 shows the result of image denoising after applying FastICA algorithm. The noise has been completely eliminated from the image and also the edge information preserved. The Fig. 4 and Fig. 5 show the result of applying wavelet and wiener filtering techniques respectively. These techniques are not able to completely filter out noise from the image. Similarly for the comparison , the performance of the other filters like average and median filters are demonstrated in Fig. 6 and Fig. 7. The results show that there is blurring effect introduced by mean and average filtering methods and hence difficult to delineate the edges of the regions in the image.

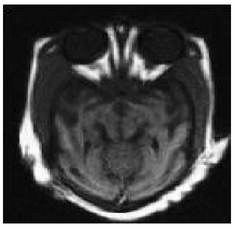

Fig. 1 Original noise free image

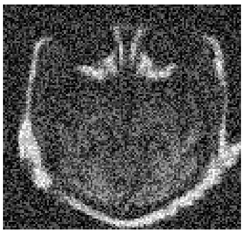

Fig. 2 Noisy image

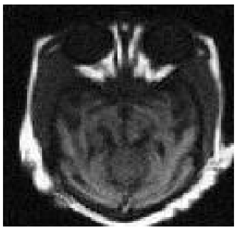

Fig. 3 ICA denoised image

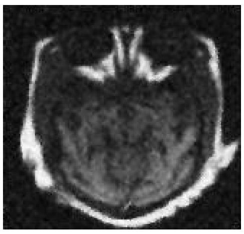

Fig. 4 Wavelet denoised image

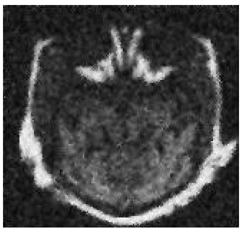

Fig. 5 Wiener denoised image

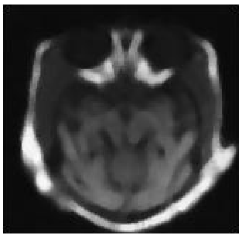

Fig. 6 Median denoised image

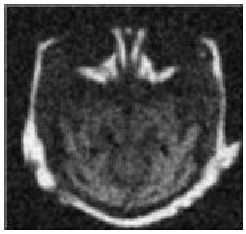

Fig. 7 Average denoised image

The analysis of the denoised image in each method is done using peak signal-to-noise ratio (PSNR), mean absolute error (MAE) and structural similarity index metrics (SSIM) which are given by the following equations as:

$$PSNR=10\log\left[\frac{255^2}{\frac{1}{M\times N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(I_{mn}-\hat{I}_{mn})^2}\right] \tag{9}$$

$$MAE=\frac{1}{MN}\sum_{n=1}^{N}\sum_{m=1}^{M}\left|I_{mn}-\hat{I}_{mn}\right| \tag{10}$$

Where I_{mn} and $\hat{I}_{mn}$ are the original and denoised images respectively. The PSNR and MAE metrics measure error between the original and the denoised image. They process all the pixels equally, so they cannot resonably reflect the subjective feeling on different scenes based on human visual sensitivity(HVS). Thus, a more comprehensive image quality assessment can be made by considering HVS. The method here is based on structural distortion measuremnt instead of error measurement. The idea behind this is that the human vision system is highly specialized in extracting structural information from the viewing field and it is not specialized in extracting errors. The structural similarity index correlates with human visual system. Thus SSIM is used as a perceptual image quality evaluation metric. The SSIM is defined as function of luminance*(l)*, contrast*(c)* and structural components*(s)* respectively[10].

$$SSIM = l(x,y).c(x,y).s(x,y) \tag{11}$$

Where,

$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1} \tag{12}$$

$$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2} \tag{13}$$

$$s(x, y) = \frac{2\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3} \tag{14}$$

The mean and variance are denoted by μ and σ. The constants C1, C2 and C3 are included to avoid numerical instabilities in the ratios. The SSIM is calculated between two NxN neighbourhoods of original and denoised images.The overall perceptual similarity of an image is obtained by taking mean of SSIM (MSSIM) of several neighbourhoods. The Table 1 shows the performance comparision of denoising methods based on estimated PSNR, MAE and SSIM values of ICA, wavelet, wiener, median and average filter. The estimated values in Table 1 indicate that the independent component analysis technique is the most effective denoising method compared to other methods. In comparision with the other methods, the image denoised by ICA has good signal - to - noise ratio and structural similarity index is almost close to that of original image. Thus ICA method provides better quality image which is close to human perception.

TABLE1
PEROFRMANCE COMPARISION OF DENOISING METHODS

Method	Peak Signal-Noise Ratio(PSNR)	Mean Absolute Error (MAE)	Mean Structural Similiraty Index Metrics(MSSIM)
ICA	25.8245	0.7312	0.9120
Wavelet	20.1586	8.2115	0.7822
Wiener	21.7831	12.1556	0.6073
Median	18.9694	22.0673	0.6989
Average	17.1122	28.6381	0.4431

The averaging and median filters have poor performance compared to other methods. Whereas wavelet and wiener filter show better denoising results in comparison with median filter but they don't preserve the edge information as lot of smoothing is done. The ICA method cancels out the noise as well as preserves the edge information. Thus retains the information of the original image. The further analysis is carried out by varying noise variance and calculating corresponding PSNR of the denoised image by different filtering techniques. The PSNR of denoised image produced by different filters for various values of noise variance is illustrated in Fig. 8. The structural similarity index correlates with human visual system. The Fig. 9 shows the plot comparing MSSSIM of denoised images of different filters. It shows that MSSIM of denoised image produced by ICA is close to the original image. Hence by comparing the various denoising methods using image quality metrics like PSNR, MAE and MSSIM, independent component analysis proves to be the effective denoising method for medical images.

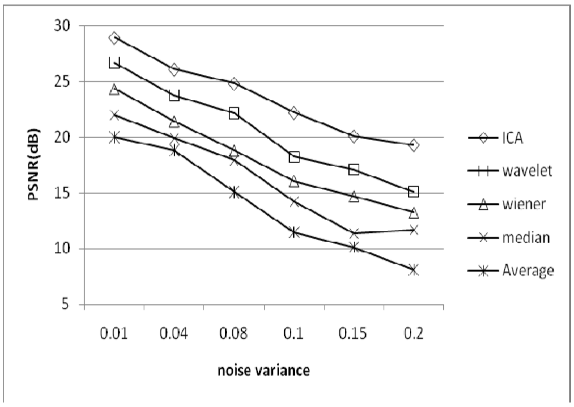

Fig 8. Comparision of PSNR values of different filters for various noise variances.

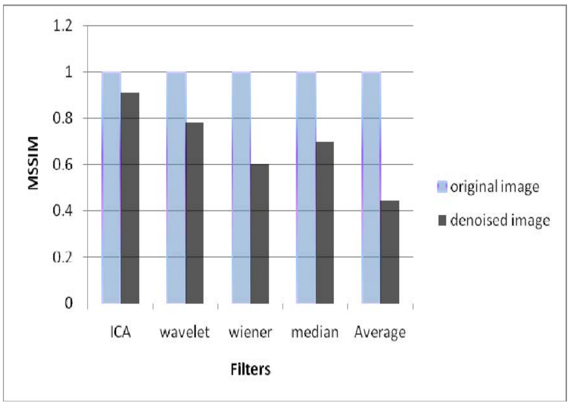

Fig 9. Comparision of MSSIM values of denoised images of different noise filters.

V. Conclusions

The denoising is one of the important tasks in medical image pre-processing in order to have a clear image for diagnosis. In this paper, a method for denoising medical images based on independent component analysis is implemented and performance analysis is made in comparison with other methods. The experimental results show that independent component analysis can effectively remove noise from the image and performs better compared to other filtering methods. Hence it helps physician in making accurate diagnosis of the disease in the early stages of deadly diseases like cancer and thus reduce the death rate.

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