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"A Novel Medical Image Blind Equalization Algorithm"

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Abstract

A novel adaptive variable step-size constant module medical CT image blind equalization algorithm was proposed. The proposed algorithm overcomes the shortcoming of conventional constant module blind equalization algorithm with the fixed iteration step-size. The processing of image restoration transformed by a linear operation is equivalent to one dimensional blind equalization. The constant modulus blind equalization cost function applied to medical CT image was founded. The mean square error was utilized as step-size control factor to speed up the convergence and improve the performance of the algorithm. Computer simulations show that new algorithm improves peak signal to noise ratio, restoration effects and efficiency of operations, and decrease state residual error.

"Keywords: Blind Equalization, Variable Step-size, Constant Module Algorithm, CT image, Mean Square Error;"

1. Introduction

Medical CT image reflects the degree that the organs and tissues absorb X-ray. It benefits discovering small lesions of microstructure in vivo. And it is a most important assistant means in the field of medical image diagnosis. However, in the process of imaging and transfer, due to the image affected the two-dimensional channel, namely point spread function, and the image blurring will carry out. The degraded CT

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images will have an influence on affecting normal display and diagnostic accuracy. Nevertheless, in nature, the process of the CT image degradation is often unknown. Blind image restoration is that, in the case of unknown degradation information, interference and noise are removed, the lost image will be recovered, and the restored image approaches the original image as much as possible.

At present, according to different recovery process, blind image restoration will be divided into parameter estimation method, non-parameter iterative method and so on. Gordana Pavlovic proposed a blind image restoration algorithm based on maximum likelihood criterion[1]. The difficulty of this method is the establishment of image probability density function. Its accuracy has a directly influence on the image restoration results. Dalong Li combined maximum likelihood estimation with support vector regression to solve blind image restoration algorithm[2]. The algorithm is robust to noise, but the training process makes the computational cost increase. Aristidis.C.Likas et al utilized machine learning mechanism to solve the model, and derived the discrete form of Bayesian model[3]. On this basis, Dimitris G. Tzikas et al estimated not only point spread function but also support domain, and proposed an improved Bayesian model to improve the robustness of the algorithm[4]. The algorithm preferably reserved the image boundary features, but the method requires a higher estimate of the model. Ming Jiang proposed a blind maximum expected restoration method, and the algorithm was applied to blind CT images restoration[5]. Zhang Hang adopted the structure of alternating minimization to solve blind image restoration problem[6]. In the fuzzy identification stage, total variation regularization algorithm was used; during the restoration stage, Weber's law and total variation regularization were combined. Kim-Hui Yap makes use of neural networks as a classifier, and each neuron's decision error is called soft decision error[7]. Establish the link between soft decision error and the traditional blind image restoration cost function. The cost function was optimized by solving soft decision error to achieve the minimum. Jonathon A. Chambers transform blind image restoration into signal classification problem in the support region[8]. The algorithm improved the convergence speed of classification by the key strategy of a resetting. In short, blind image restoration algorithm has been widely used, and in-depth researched. This paper utilized a signal transformation, and blind equalization technique of signal processing was applied to CT medical image restoration.

Without any training sequence, blind equalization algorithm only makes use of receiving sequence’s transcendent knowledge to poise the idiosyncrasy of channel and make the output sequence of equalizer be close to the sending sequence. It is an important frontier hot research topic in the domain of communication, signal and information processing, detection theory and other disciplines. In the existing blind equalization algorithm, the most widely used algorithm is the constant modulus blind equalization algorithm, which generally adopts a fixed step size, and the convergence speed and steady-state residual error become contradictory. Constant modulus algorithm is a classical algorithm[9], and it was widely used in various field of blind equalization. This paper utilized the similarity between the process of image degradation and inter-signal interface. On the base of the literature[10], a variable step-size constant modulus image blind equalization algorithm based on dimension reduction was proposed. Dimension reduction was used to complete transforming from two-dimensional image signal into a one-dimensional complex signal sequence. The constant modulus cost function was established. The strategy of variable step-size was introduced to improve the convergence properties of constant modulus algorithm. The optimal estimation of the dimension reduction signal was obtained, and then images estimate were obtained by dimension rising. The method completed the restoration of the image by sophisticated constant modulus blind equalization algorithm, avoided the two-dimensional matrix inverse iteration operation, reduced the complexity of the algorithm, and effectively eliminated the impact of the point spread function. Image restoration has well been carried out. Simulation results verify the effectiveness of the algorithm.

2. Math model

Degraded image g_{ij} is engendered the original image f_{ij} that passes a point spread function system h_{ij}, and it was added by noise n_{ij}. In order to facilitate the discussion, set the point spread function is a linear time-invariant system.

$$g_{ij} = f_{ij} * h_{ij} + n_{ij} = \sum_{u=0}^{A-1}\sum_{v=0}^{A-1} f_{u,v} h_{i-u,j-v} + n_{ij} \tag{1}$$

Where, $i, j = 0,1,2\cdots M-1$, $A \times A$ is size of point spread function.

In order to utilize blind equalization technology pass to realize medical CT image restoration, firstly, two-dimensional medical CT images should be transformed into one-dimensional row or column sequence. However, a single row or column transform weakened blind equalization algorithm's ability that overcomes point spread function's affect. This paper proposed an image blind equalization based on simultaneous row and column signal transform. The block diagram is shown in Fig.1.

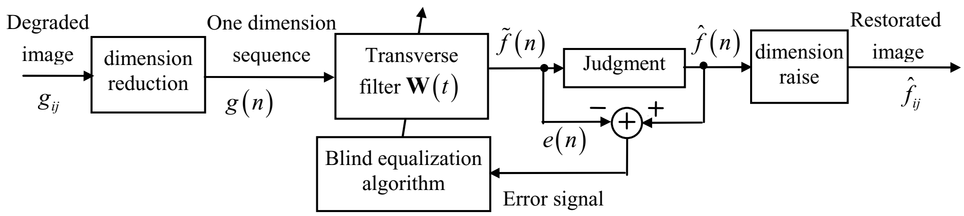


Fig. 1. Principle block diagram of blind equalization algorithm

In the Fig.1, $\mathbf{W}(n)$ is the weight vector of blind equalizer; $g(n)$ is one-dimensional signal sequence that the image was transformed into by dimension reduction; $\tilde{f}(n)$ is the restoration signal of blind equalizer output; $\hat{f}(n)$ is the output of the estimator; $\hat{f}_{ij}$ is the estimator of the image.

In the process of image dimension reduction by row transform, so that

$$g(n) = g_{ij} \tag{2}$$

Where, $n = 0,1,2,\cdots, M^2-1$; $j = ((n))_M$, $M \times M$ is the size of image. $((n))_M$ is the remainder operation expression, and it expresses the residual value of n module M; $iM + j = n$.

The transversal filter in the algorithm is expressed as

$$\mathbf{W}(n) = \left[w_0(n),\cdots,\ w_r(n),\ ,\cdots,\ w_{L-1}(n)\right]^{\mathrm{T}} \tag{3}$$

Then

$$\tilde{f}(n) = \sum_{r=0}^{L-1} w_r(n) g(n-r) \tag{4}$$

In order to satisfy equation (4), the input sequence vector $\mathbf{G}(n)$ of the transversal filter is expressed as

$$\mathbf{G}(n) = \left[g(n), g(n-1),\cdots,\ g(n-L+1)\right]^{\mathrm{T}} \tag{5}$$

Thus, equation (4) can be written as

$$\tilde{f}(n) = \mathbf{W}^{\mathrm{T}}(n)\mathbf{G}(n) \tag{6}$$

In order to obtain the optimal image and the optimal solution of $\mathbf{W}(n)$, its solution is similar to one-dimension equalization. Image was carried out by dimension reduction to solve $\mathbf{W}(n)$. The cost function of $\mathbf{W}(n)$ was established and optimized to obtain the optimization solution. To obtain the restoration image, firstly, the corresponding restoration sequence $\hat{f}(n)$ was obtained, and then the corresponding estimate of the image by inverse transform is obtained, that

$$\hat{f}_{ij} = \hat{f}(n) \tag{7}$$

Where, $n = 0,1,2,\cdots,\ M^2-1$; $j = ((n))_M$, $iM + j = n$.

3. Variable Step-Size CMA CT image blind equalization algorithm

Digital medical CT images are grayscale, and independent with the distribution [11]. C. Vural firstly proposed a two-dimensional constant modulus cost function to realize image restoration. In this paper, the ideological dimension reduction was adopted. The newly CMA cost function is

$$J(n) = \mathrm{E}\left[\left(\left|\tilde{f}(n)\right|^2 - R_2\right)^2\right] \tag{8}$$

Where, R_2 depends on fourth-order statistics of one-dimensional signal sequence formed by two-dimensional image. When statistical information of the image is known, R_2 is a constant.

In practice, the expectation value of variable can not been calculated. The instantaneous value of the solution often was utilized to replace the statistical average value. The above equation can be transform into,

$$J(n) = \left[\tilde{f}^2(n) - R_2\right]^2 \tag{9}$$

According to LMS method, weight iteration formula of medical CT images constant modulus blind equalization based on row-column transform were obtained.

$$w_r(n+1) = w_r(n) - \mu \frac{\partial J(n)}{\partial w_r(n)} \quad r = 0,1.\cdots,L-1 \tag{10}$$

Where, μ is the step factor.

From equation (10) can be obtained

$$\frac{\partial J(n)}{\partial w_r(n)} = \left[\tilde{f}^2(n) - R_2\right]\tilde{f}(n)\frac{\partial \tilde{f}(n)}{\partial w_r(n)} = \left[\tilde{f}^2(n) - R_2\right]\tilde{f}(n) g(n-r) \tag{11}$$

Iterative weight vector can be described by the vector form as following.

$$\mathbf{W}(n+1) = \mathbf{W}(n) - \mu\left[\tilde{f}^2(n) - R_2\right]\tilde{f}(n)\mathbf{G}(n) \tag{12}$$

The shortcoming of the traditional constant modulus algorithm is slow convergence. From equation (12) can be seen, the algorithm adopted a fixed step size. The larger step size is, the quicker convergence speed is, but the larger step size causes large steady residual error. The small step size can reduce steady residual error and increase the convergence precision, but at one time it depresses convergence speed and tracking capacity, or even results in divergence algorithm. In order to resolve the contradiction, the fixed step size was replaced by a variable step size. Variable step size image blind equalization algorithm was put forward. In the other word, the step size was increased during the diffusion of the algorithm; the step size was reduced after the convergence of the algorithm to improve the accuracy of convergence.

In order to achieve variable step size constant modulus blind equalization algorithm, the step size factor μ should be a function of a variable parameter, and during the convergence of algorithm, the parameter possesses gradually change in the trend.

In constant module blind equalization algorithm, variable step-size $\mu(n)$ controlled by mean square error takes the place of fixed step-size

$$\mu(n) = \alpha E\left[e^2(n)\right] \tag{13}$$

Where, $e(n)$ is error signal, α is scale factor and it is used to control the range of step-size $\mu(n)$.

$$e(n) = \hat{f}(n) - \tilde{f}(n) = \hat{f}(n) - \mathbf{W}^{\mathrm{T}}(n)\mathbf{G}(n) \tag{14}$$

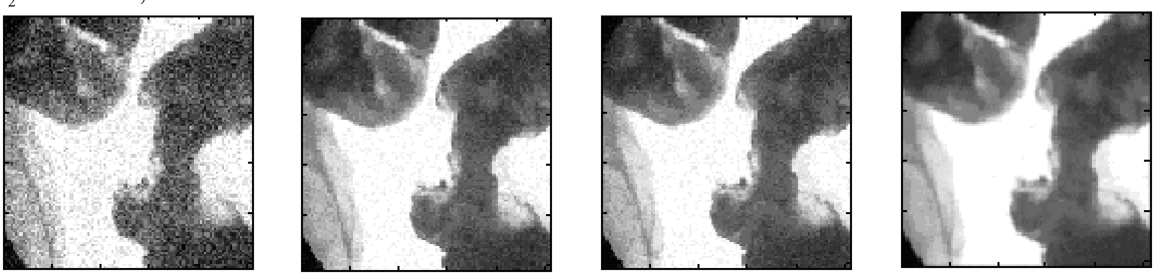
The variable step size constant modulus algorithm blind equalization based mean square error was obtained. Then

$$\mathbf{W}(n+1) = \mathbf{W}(n) - \alpha E\left[e^2(n)\right]\left[\tilde{f}^2(n) - R_2\right]\tilde{f}(n)\mathbf{G}(n) \tag{15}$$

By equation (15), the optimal estimation of dimension reduction sequence can be obtained, and the optimal estimation of the reconstructed image was obtained. However, in order to ensure effective convergence of the algorithm, the maximum step size must not exceed the upper limit of step factor, and thus the parameter value of should be reasonably selected.

4. Experimental simulation

In order to validate the algorithm, the experiment adopted 8-bit, the size of 256 × 256, CT images. The degradation of CT image is an approximate Gaussian process[12], the point spread function is taken as 15 × 15 Gaussian matrix, and its variance is 0.1. The original image passed through the point spread system, and the degraded image was added by Gaussian white noise with mean 0 and variance 0.008. And it was shown in Fig.2(a). In the simulation, the order of the transversal filter is 21, and its initial value was $\left[0,\cdots,0,1,0,\cdots0\right]^{\mathrm{T}}$; $R_2 = 39320.0$; $\alpha = 0.05$.



(a) Degraded image (b) Result of IBD method (c) Result of CMA (d) Result of this paper

Fig. 2. Principle block diagram of blind equalization algorithm

The iterations number of IBD is 100, the result is shown in Fig.2(b). Fig.2(c) is the restoration of constant modulus blind equalization algorithm. Fig.2(d) is the restoration image of the proposed variable step size CMA blind equalization algorithm.

5. Conclusion

Constant modulus blind equalization algorithm in the communication system was applied to blind image restoration. Firstly, dimension reduction was utilized to transform the image into one-dimensional signal. The cost function of constant modulus applied to image restoration was constructed. In order to overcome the defects of constant modulus algorithm, slow convergence, the mean square error signal was utilized to control step size factors, speed up the convergence rate. Simulation results show the effectiveness of the algorithm, the algorithm not only gets better in the restoration effect and improves the peak signal to noise ratio, and obtains better convergence. The improved algorithm adopts variable step-size and resolves the conflict between convergence speed and state residual error in conventional constant algorithms. Theory analysis and simulation indicate this algorithm has smaller state residual error and faster convergence speed.

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