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Sparse deconvolution method for ultrasound images based on automatic estimation of reference signals

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ABSTRACT

Sparse deconvolution is widely used in the field of non-destructive testing (NDT) for improving the temporal resolution. Generally, the reference signals involved in sparse deconvolution are measured from the reflection echoes of standard plane block, which cannot accurately describe the acoustic properties at different spatial positions. Therefore, the performance of sparse deconvolution will deteriorate, due to the deviations in reference signals. Meanwhile, it is inconvenient for automatic ultrasonic NDT using manual measurement of reference signals. To overcome these disadvantages, a modified sparse deconvolution based on automatic estimation of reference signals is proposed in this paper. By estimating the reference signals, the deviations would be alleviated and the accuracy of sparse deconvolution is therefore improved. Based on the automatic estimation of reference signals, regional sparse deconvolution is achievable by decomposing the whole B-scan image into small regions of interest (ROI), and the image dimensionality is significantly reduced. Since the computation time of proposed method has a power dependence on the signal length, the computation efficiency is therefore improved significantly with this strategy. The performance of proposed method is demonstrated using immersion measurement of scattering targets and steel block with side-drilled holes. The results verify that the proposed method is able to maintain the vertical resolution enhancement and noise-suppression capabilities in different scenarios.

1. Introduction

Ultrasound imaging plays a significant role in ultrasonic NDT, profiting from the abundant and quantitative information of the objects under inspection [1]. The low resolution of ultrasonic imaging techniques restricts their practical performance in industry despite the promising perspectives they suggest in accurately inspecting. For this reason, the researches on enhancing the image resolutions attract great interest in ultrasonic community [2,3].

In the case of ultrasonic B-scan images, which are composed of reflection echoes acquired from different points along the horizontal axis, the lateral resolution can be significantly improved by using the synthetic aperture focusing technique (SAFT) and many algorithms have been developed to implement such technique [4,5]. Generally, the vertical resolution of ultrasonic B-scan images is enhanced by deconvolution methods, which include two main categories: the non-blind and the blind deconvolution. Although the blind deconvolution method has successfully bolstered the medical applications [6,7], the non-blind deconvolution is more widespread in the industrial field, due to its advantages in terms of robustness and computation efficiency. To solve non-blind deconvolution, a number of algorithms have been employed, such as Wiener filter [8], matching pursuit (MP) [9–11], basis pursuit (BP) [12,13] and others [14,15]. In many practical non-destructive testing applications, the defects in an object are generally finite in number and their distribution can be assumed sparse. Therefore, sparse non-blind deconvolution could be applied [16]. For simplicity, sparse non-blind deconvolution is referred as sparse deconvolution in the following content. Benefiting from the sparsity of ℓ_1 norm regularization, sparse deconvolution with BP algorithm has been widely applied for NDT [17–19]. Recently, it has been implemented through the separable approximation (SpaRSA) algorithm [20], leading to a simultaneous improvement of lateral and temporal resolution [21].

However, the convergence and accuracy of sparse deconvolution heavily depend on the reference signals, which are commonly measured from the reflection echoes of standard plane block. The

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measured reference signals are usually approximated, since they are not taking into account the acoustic properties, which are varying with spatial positions [22,23]. Moreover, the reference signals must be manually remeasured when the inspection object is changed, thus the development of automatic ultrasonic NDT is severely hindered. It is therefore highly desired to automatically acquire the reference signal of higher accuracy.

In this paper, a sparse deconvolution method based on automatic estimation of reference signals is proposed. Firstly, the ultrasonic B-scan image is decomposed into A-scan signals, which are the time histories of received ultrasonic echoes. Then, Fourier transformation is applied to the A-scan signals to generate amplitude spectra, and the estimated reference signals are derived from the expectation values of the amplitude spectra. The SpaRSA algorithm with soft thresholding and gradient descent is then applied to acquire the sparse results of A-scan signals column by column. Finally, the new ultrasonic B-scan image is reconstructed from those sparse results.

Based on the assumption of sparse distribution of defects in industrial NDT application and automatic estimation of reference signals, a regional strategy could be implemented to suppress the inaccuracy of spatially varied reference signals. The ultrasonic B-scan images are firstly decomposed into smaller binary ones and the boundaries are traced out. The regions of interest (ROI) are then selected by the thresholds of area. Finally, the reference signal matrix of each ROI is estimated, and the SpaRSA algorithm is applied to realize the regional and eventually global sparse deconvolution. Moreover, the image dimensionality is significantly reduced with this strategy, and the computation efficiency is therefore improved.

The rest of the paper is organized as follows. The theory of sparse deconvolution based on automatic estimation of reference signals is presented in Section 2, including the model of sparse deconvolution and its solution, the estimation of reference signal matrix and the realization of regional sparse deconvolution. In Section 3, the experiments of ultrasonic B-scan imaging are carried out to demonstrate the performance of proposed method. The conclusion and discussion are in Section 4.

2. Theory

2.1. Sparse deconvolution model and its conventional solution

Before deriving the sparse deconvolution based on automatic estimation of reference signals, the sparse deconvolution model and its conventional solution are briefly introduced. According to the model from the first-order Born approximation of the wave equation, the A-scan signal of reflection echo can be expressed by a convolution of the reference signal and the reflectivity function as follows

$$\boldsymbol{y} = \boldsymbol{x} * \boldsymbol{h} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{y} = [y(0), y(1), \ldots, y(M-1)]^T$, $\boldsymbol{x} = [x(0), x(1), \ldots, x(M-1)]^T$, $\boldsymbol{h} = [h(0), h(1), \ldots, h(M-1)]^T$ and $\boldsymbol{n} = [n(0), n(1), \ldots, n(M-1)]^T$ denote the A-scan signal of reflection echo, reference signal, reflectivity function and noise, respectively. After convolution of $\boldsymbol{x} * \boldsymbol{h}$, the reflection echo is shifted, and the other elements in the array from M to $2M-1$ are zero. Thus, the first M elements of convolution result are truncated in Eq. (1).

In the frequency domain, the Fourier amplitude spectrum of reference signal can be calculated by [24]

$$||\boldsymbol{X}|| = ||\boldsymbol{F}\boldsymbol{x}||, \tag{2}$$

where $\boldsymbol{X}$ is the Fourier transform of $\boldsymbol{x}$, $||.||$ denotes the magnitude of complex number, and $\boldsymbol{F}$ is Fourier matrix, which is given as

$$\boldsymbol{F} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & \omega & \cdots & \omega^{M-1} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \omega^{M-1} & \cdots & \omega^{(M-1)(M-1)} \end{bmatrix}, \quad \omega = e^{-j2\pi/M}$$

In general, a vertical shift of deconvolved image may appear after deconvolution. To avoid this shift, phase spectrum of $\boldsymbol{x}$ is required to be zero. With this assumption the reference signal matrix can be written as

$$\boldsymbol{C} = \frac{1}{M}\boldsymbol{F}^{\dagger} diag(||\boldsymbol{X}||)\boldsymbol{F}, \tag{3}$$

where diag $(||\boldsymbol{X}||)$ is a diagonal matrix which diagonal contains the elements of the vector $||\boldsymbol{X}||$ and $\dagger$ represents a conjugate transpose. According to the convolution theorem, the multiplication of matrix $\boldsymbol{C}$ and vector $\boldsymbol{h}$ is equal to the convolution of $\boldsymbol{x}$ and $\boldsymbol{h}$ in time domain. Thus, Eq. (1) can be rewritten as

$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{h} + \boldsymbol{n}. \tag{4}$$

Then, the objective function can be formulated as follows

$$\min_{\boldsymbol{h}} ||\boldsymbol{y} - \boldsymbol{C}\boldsymbol{h}||_2^2, \tag{5}$$

where $||.||_2$ denotes the Euclidean norm.

The sparse deconvolution of A-scan signal without noise can be solved through Eq. (5) when $\boldsymbol{x}$ and $\boldsymbol{y}$ are known. However, the optimization problem of Eq. (5) is ill-posed when the noise is considered, and its solution will be not sparse. It is therefore necessary to adopt ℓ_1 regularization [25] to regularize Eq. (5) as

$$\min_{\boldsymbol{h}} ||\boldsymbol{y} - \boldsymbol{C}\boldsymbol{h}||_2^2 + \mu||\boldsymbol{h}||_1, \tag{6}$$

where $||\boldsymbol{h}||_1$ represents the ℓ_1 regularization and μ is the regularization parameter, which introduces a trade-off between the least-square fit and the penalty from adjusting the sparsity of $\boldsymbol{h}$. When μ become larger, the solution will be sparser, and vice versa. Generally, μ is set to 0.2, for that the solution of Eq. (6) would be distorted if μ is too large.

After Eq. (6) is established, the sparse deconvolution of A-scan signal becomes a nonlinear optimization problem. Due to the special convexity of ℓ_1 regularization, the classical nonlinear optimization algorithms which require Hessian and Gradient matrix as the basis, are difficult to solve. Hence, the SpaRSA algorithm is adopted to solve this problem and the detailed procedures are shown in Fig. 1.

There are three basic steps in the SpaRSA algorithm, which are gradient descent, soft thresholding and variable step-length strategy. In the first step, the gradient descent function G is defined as follows

$$\boldsymbol{z}_k = G(\boldsymbol{h}_k) = \boldsymbol{h}_k - \boldsymbol{C}^T(\boldsymbol{C}\boldsymbol{h} - \boldsymbol{y})/\alpha_k, \tag{7}$$

where k is the number of iterations, α_k is the step-length factor, $\boldsymbol{z}$ is the intermediate variable and T is the transpose symbol.

Then, the soft thresholding is defined as

$$J(\boldsymbol{z}, \lambda) = sign(\boldsymbol{z}) \cdot max\{|\boldsymbol{z}| - \lambda, 0\}, \tag{8}$$

where λ is the soft threshold and $sign(.)$ represents the sign function. When λ is set as μ/α_k, the iteration of $\boldsymbol{h}$ can be described as

$$\boldsymbol{h}_{k+1} = J(\boldsymbol{z}_k, \mu/\alpha_k) = sign(\boldsymbol{z}_k) \cdot max\{|\boldsymbol{z}_k| - \mu/\alpha_k, 0\} \tag{9}$$

Due to the weak correlation between noise and reference signal matrix, the energy distribution of noise will be scattered after it is mapped on the sparse basis. Therefore, the soft thresholding is able to denoise the signal.

To implement the variable step-length strategy, the range is firstly determined by the Barzilai–Borwein method [26] and the