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Effect of different algorithms on nondestructive signal detection

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Abstract. In order to reduce a lot of noise in the ultrasonic signals in the process of online collection and solve the material internal defect diagnosis accuracy problem, the ultrasonic echo signal denoising algorithm combining the generalized K-singular value decomposition (K-SVD) and orthogonal matching pursuit algorithm (OMP) is studied. This algorithm uses the K-SVD algorithm to train the Gabor dictionary into the rather complete dictionary that can effectively reflect the signal structural characteristics. And then, based on the rather complete dictionary completed by training, OMP algorithm is used to form a linear combination of the original signal of a certain number of dictionary atoms, so as to realize signal denoising. Through the simulation experiment, this method is compared with the traditional wavelet threshold value denoising method. The experimental results show that the method is better than wavelet threshold denoising method in terms of ultrasonic echo signal denoising effect, and the larger the noise is, the more obvious the comparison is. To sum up, it not only can effectively filter out the Gauss white noise and improve the signal-to-noise ratio, but also can retain the useful information of the original signal as much as possible.

Key words. ultrasonic signal, wavelet de-noising, K-SVD algorithm, signal feature.

1. Introduction

In ultrasonic non-destructive testing technology, the echo signal contains a lot of useful information, but the reason for instrument noise, noise, noise coupling and ultrasonic reflection, scattering and so on will include a lot of noises in echo signal. It seriously interferes with extracting useful signals, and affects the insufficiency detection results, leading to missed and false detection (Khawne, 2015). Therefore, effective signal processing methods must be used to suppress all kinds of noises and improve the signal-to-noise ratio, so as to improve the quality of detection and the

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accuracy of analysis. In the field of ultrasonic echo signal processing, the methods of split spectrum and wavelet analysis have achieved good results, but there are also some limitations (Yoshizawa, 2016). The number of filters, the bandwidth and the frequency interval between filters will have a great impact on the split spectrum denoising. Wavelet analysis will lose a small amount of useful information in the process of denoising, which will damage the signal characteristics (Sumiya, 2016).

Michal Aharon and others put forward a dictionary training algorithm, that is, K-SVD algorithm, which is widely used in signal, image and other fields, and has achieved excellent results (Chen, 2017). Through this algorithm, we can train the dictionary reflecting the characteristics of the signal and get the dictionary that can best express the characteristics of the signal. The orthogonal matching pursuit (OMP) provides an over complete dictionary. OMP algorithm uses the atomic selection criteria in the matching pursuit algorithm (MP), for the orthogonal processing of selected atomic set, so as to be approximate to the optimal solution and reduce the number of iterations. The linear combination of few atoms is used, which can accurately represent the signal features. The K-SVD algorithm and OMP algorithm are applied to denoise the ultrasonic echo signal, and compared with the wavelet denoising method. The experimental results prove the superiority of the algorithm.

2. THEORIES

2.1. Space domain denoising technology

This kind of algorithm is used to denoise directly in the image space domain. The basic idea of the algorithm is to first defining the template, then adjust the gray value of the pixels in the template by analyzing the gray level of pixels in the target pixel field. Then, we move the template and repeat the adjustment process until the requirements are met. This kind of algorithm can be divided into linear denoising algorithm and nonlinear denoising algorithm (Grohmann, 2016).

The most typical denoising algorithm in the linear denoising algorithm is the mean denoising algorithm, which processes all pixels in the gray mean. Therefore, the denoising is blindness, which seriously damages the details of images, resulting in blurred images (Mor, 2015). Scholars have proposed many improved algorithms on the basis of mean algorithm, but the effect of denoising is always not ideal. Nonlinear denoising algorithm is proposed to set the median algorithm for image denoising algorithm based on the boom. It is proved that the median algorithm can completely solve the fuzzy boundary problem of linear algorithm, so it is important in the study history of the noise reduction algorithm in image (Yoshizawa, 2016). The basic idea of the median algorithm is to sort the gray in all the pixels in the template, and then use the sorted median gray values to replace target pixel gray value. The idea skillfully suppresses impulse noise, and can effectively protect the edge information of the image (Sauer, 2016). However, many shortcomings of the median algorithm are not to be ignored. For example, its ability to suppress Gauss noise and uniform noise is not strong, and the ability of denoising is greatly influenced by the noise density, which destroys the detail information, such as sharp edges and corners. Since then, many improved median algorithms have been proposed, such as denoising algorithm, switch median denoising algorithm, multipole median denoising algorithm, variable window length median denoising algorithm and so on.

2.2. Transform domain denoising technology

The main idea of this algorithm is to transform the image, so as to obtain its expression in the transformation domain. Then, it processes the coefficient of image in the transformation domain, and finally gets the form of image in the spatial domain by inverse transformation, so as to achieve the purpose of denoising. This representation often shows the structural features of the image more intuitively, and is more conducive to the separation of noise (Grennberg, 2015). Image denoising algorithm based on Fourier transform, wavelet transform, wavelet packet transform and discrete cosine transform is an important member of image denoising algorithm in transform domain (Zhang, 2017). Wavelet transform can well characterize the non-stationary characteristics of one-dimensional signals, and has the advantage of multi-resolution. The coefficients obtained by wavelet decomposition of signals are sparse, which is conducive to extract signal characteristics and remove signal noise. And different small wave bases can be selected for different signals to get good treatment effect.

However, the two-dimensional wavelet bases generated by tensor product of one-dimensional wavelet do not satisfy the anisotropic scaling relations, and cannot sparsely represent two-dimensional images containing line or surface singularity (Nakayama, 2016). To this end, the Multiscale Geometirc Analysis (MGA) method is proposed. Compared with the wavelet transform, MGA can represent the image more sparsely, and then obtain better denoising effect. However, a multi-scale geometric analysis method can only represent some features of the image, while natural images usually contain various features. Therefore, it is difficult to represent all the features effectively by using one transformation (Zhihong, 2016). Since the proposal of the over complete dictionary sparse representation of the concepts mentioned, this area is developing rapidly. In the past years, researchers have proposed many signal sparse representation and approximation methods for image denoising research, which has achieved a lot of effects better than the previous image denoising results (Poudel, 2015). In addition to the denoising algorithm, there are many scholars exploring the image denosing algorithm from the perspective of intelligent algorithm, mathematical morphology and information theory. And it generates the image denoising algorithm based on mathematical morphology, image denoising algorithm based on fuzzy denoising and image denoising algorithm based on information entropy and so on.

2.3. K-SVD noise suppression method based on signal redundancy

At present, a new "dictionary learning method" has been widely researched and applied in image processing. Its core is the training process of dictionary, which is called K-SVD algorithm. This algorithm is first proposed by Aharon, Elad and so on. The research shows that K-SVD method not only effectively suppresses additive Gauss white noise, but also preserves important information such as edge and texture, especially for texture image processing. In addition, this method has good adaptability (Hasegawa, 2016). However, the K-SVD algorithm is designed for additive noise, while the coherent speckle of SAR image is multiplicative noise (Sinding, 2016). The K-SVD algorithm directly applied to image speckle will appear over smooth phenomenon. In order to overcome this shortcoming, many scholars have adopted the logarithmic transformation strategy. That is, first of all, the image is conducted with the logarithmic transformation, the multiplicative noise model is transformed into additive, and then the K-SVD algorithm is used to denoise the log image. Finally, transform image can be obtained after despeckling. That is to say, after the logarithmic transformation of the image, the noise is not zero mean, which results in the bigger difference between the mean value and the radiation characteristic of the original image. In addition, it does not satisfy the requirement that noise is zero mean additive Gauss noise in the K-SVD algorithm. To this end, the objective function of the K-SVD algorithm is weighted and enhanced to improve the effect of the speckle reduction (Liang, 2015). However, for the images with low number of visions, the speckle noise will affect the training of dictionaries, so there are still a lot of speckle noises in the final results, and the edges are blurred.

3. METHODOLOGY

3.1. Super complete dictionary training based on K-SVD algorithm

The super complete dictionary is an important research content in sparse representation of signal / image. To a large extent, it determines whether the feature of signal can be effectively expressed. Therefore, we choose the Gabor atom library which is close to the ultrasonic echo signal as a prior sample. In order to better express the signal features, the K-SVD algorithm is used to update the Gabor atom library adaptively.

The expression of the Gabor function is shown in formula (1):

$$g_\gamma(t) = \frac{1}{\sqrt{s}} g\left[\frac{t-u}{s}\right] \cos(vt+w) \tag{1}$$

In (**??**)1), $g(t)$ suggests the Gauss window function , γ indicates time frequency parameter and s represents the scale factor, which determines the function energy distribution rate;u refers to the shift factor, which determines the wave position; v denotes the frequency modulation factor, which decides the function main frequency; w indicates the phase factor, which determines the phase of function. From the above four time frequency parameters, Gabor atomic library can be constructed, namely Gabor dictionary:

The implementation of K-SVD algorithm is:

First of all, we set:

$$\begin{aligned} & D \in R^{n \times k}, y \in R^{n}, x \in R^{n \times k} \\ & Y = \{y_i\}_{i=1}^{N}, X = \{x_i\}_{i=1}^{N} \end{aligned} \tag{2}$$

In (??)2), D suggests Gabor dictionary, y refers to the training signal, x represents the sparse expression coefficient vector of training signal (calculated by OMP algorithm), $Y = \{y_i\}_{i=1}^{N}$ N denotes N training signal set, $X = \{x_i\}_{i=1}^{N}$ Y denotes the solution vector set of Y and R^n means the n dimension signal set.

$$\begin{aligned} & \min_{x_i} \left\{ \|y_i - Dx_i\|_F^2 \right\}, \\ & s.t \forall i, \|x_i\|_0 \leq T_0, i = 1, 2, ..., N. \end{aligned} \tag{3}$$

In (??)3), T_0 refers to the upper limit of non-zero sparse expression coefficient vector.

Secondly, we start to train the dictionary$D$. We set d_k as the k-th column vector of the dictionary to be trained. For the k-th column vector of the dictionary to be trained, the signal decomposition can be expressed as:

$$\|Y - DX\|_F^2 = \left\|E_k - d_k x_T^k\right\|_F^2 \tag{4}$$

In (??)4), x_T^k suggest the row vector in the corresponding coefficient matrix of d_k and E_k refers to the decomposition error of signal set after removingd_k.

At this point, we need to introduce the definition of four parameters, as shown in formula (??)5) and (??)6), so as to make SVD decomposition.

$$w_k = \left\{ i \left| 1 \leq i \leq K, x_T^k(i) \neq 0 \right. \right\} \tag{5}$$

$$x_R^k = x_T^k \Omega_k, Y_k^R = Y \Omega_k, E_k^R = E_k \Omega_k \tag{6}$$

In the above formula, the set w_k indicates the index set in signal decomposition, Ω_k represents $N \times |w_k|$ matrix and x_R^k, Y_k^R, E_k^R denotes the set of the results of its contraction. (??) can be transformed as:

$$\left\|E_k \Omega_k - d_k x_T^k \Omega_k\right\|_F^2 = \left\|E_k^R - d_k x_R^k\right\|_F^2 \tag{7}$$

At last, E_k is conducted with SVD decomposition. According to the above process, the column of D is updated in turn until the new dictionary D is generated. Figure 1 show the flow chart of K-SVD algorithm.

3.2. Ultrasonic echo signal processing algorithm based on OMP algorithm

Step 1: set the mixed noise signal Y, super complete dictionary D after training and spare times k.

Step 2: initialize the parameter, residual $r_0 = y$, decomposition coefficient $\hat{x} = 0$, index set $t_0 = []$, sub dictionary $T_0 = []$, iteration factor $l = 1$ and the maximum

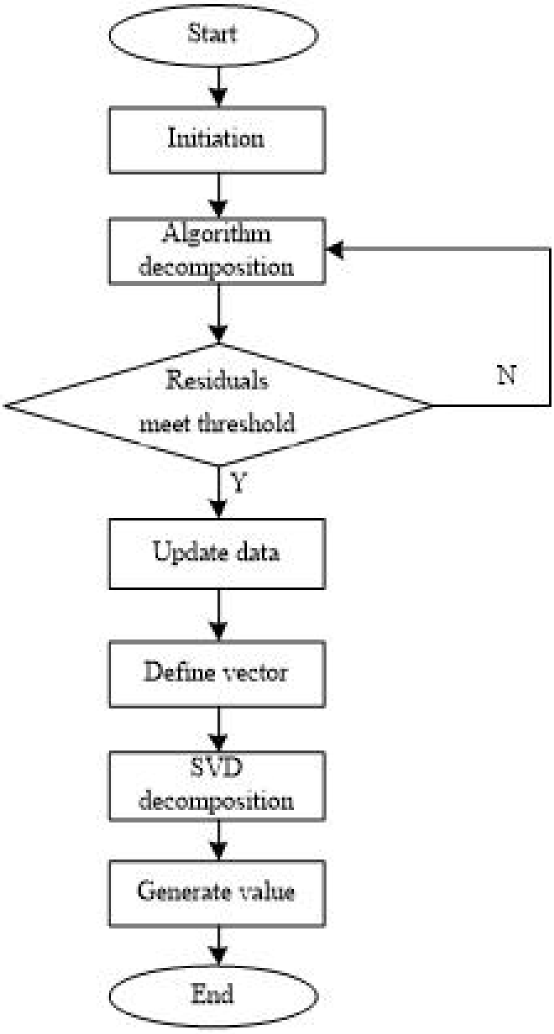

Fig. 1. K-SVD algorithm flow chart

iteration times $iterNum = k$.

Step 3: iteration process. In the l-th cycle ($l \geq 1$), operate the following formulas.

Find the best atomic index with the relative maximum calculation:

$$i_l = \arg\max_i(|d_i, r_{l-1}|), i = 1, 2, ..., N. \tag{8}$$

Update the set of atomic index:

$$t_l = t_{l-1} \bigcup i_l \tag{9}$$

Update the sub dictionary:

$$T_l = T_{l-1} \bigcup d_{i_l} \tag{10}$$

Update the coefficient estimation:

$$\hat{x}[t_l] = T_l^{+} y \tag{11}$$

Update the residual:

$$r_l = y - T_l(T_l^{+} y) \tag{12}$$

Judge the termination condition. If l > K, the algorithm ends.

Step 4: output the decomposition coefficient.

Step 5: use K-SVD algorithm to train the super complete dictionary and the output decomposition coefficient to integrate the denoising signal. Figure 2 is the OMP algorithm flow chart.

$$y = \tilde{D}\hat{x} \tag{13}$$

4. EXPERIMENTS

4.1. Experimental objective

In order to study the application effect of ultrasonic echo signal denoising based on the combination of K-SVD algorithm and OMP algorithm, the wavelet threshold method is compared and analyzed. The Gauss envelope function is used to construct the ultrasonic echo signal as input, and different SNR Gauss white noise is added for the simulation experiments. The experiment uses wavelet hard threshold method, wavelet soft threshold method and the new method in this paper to process the simulation signal containing noise, and then compares the denoising effects of 3 denoising methods. The wavelet basis used in wavelet threshold denoising is db8 wavelet with better denoising effect for ultrasonic echo signal. Finally, in this paper, the actual ultrasonic detection signal in the previous study is used as input to compare the denoising effect.

4.2. Experimental process

The denoising of simulated ultrasonic signal with signal-to-noise ratio of 10dB is as follows: first of all, we use the Gauss envelope function to build the approximate waveform of ultrasonic echo signal as the original noiseless signal, and the amplitude of the signal is based on the original signal amplitude detection. Then, the original signal is added with the the Gauss signal with signal-to-noise ratio of 10dB, that is, the noise forms the original noise containing signal. In the denoising of the noise signal with the SNR of 10dB, the wavelet hard threshold denoising method, the wavelet soft threshold denoising method and the new method proposed in this paper are adopted. The results show that the wavelet threshold denoising method can remove the noise in the signal very well, but there are still a few small noises

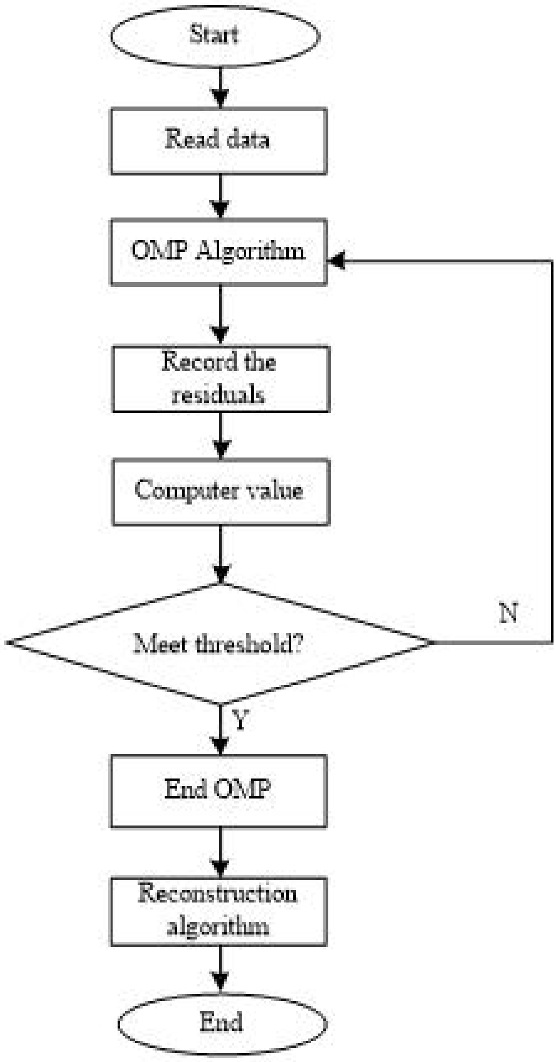

Fig. 2. OMP algorithm flow chart

that are not removed, resulting in that the waveform is not smooth enough. The denoising effect of the denoising method proposed in this paper is better, and the noise interference is completely removed.

The denoising of simulated ultrasonic signal with signal-to-noise ratio of -5dB is as follows: -5dB SNR Gauss white noise is added to the original signal to form the signal with noise. The original signal with noise is to simulate the situation when the noise is going to submerge the useful signal. As a result, how to effectively remove noise from useful signal is very important at this time. The results show that the denoising effect of wavelet hard threshold de-noising and wavelet soft threshold denoising is lower when the SNR of original signal is low, and the noise cannot be well removed. This method can still remove noise effectively and extract useful signals.

The denoising of simulated ultrasonic signal with signal-to-noise ratio of -10dB is as follows: in the original signal, the noise is added for the observation of the denoising effects of three methods. The Gauss white noise with -10dB SNR is added to the original signal and form the original signal with noise. The noise has completely submerged the useful signal. The results show that the wavelet hard threshold denoising method and the wavelet soft threshold denoising method have been seriously distorted, but the method in this paper can still extract useful signals. The experiment fully shows that this method has excellent effect in ultrasonic echo signal de-noising.

4.3. Experimental results

When the signal-to-noise ratio of the noisy signal varies from -10dB to 10dB, the comparison diagram of the reconstruction error is shown as in Figure 3. The results show that the reconstruction error of this method is lower than that of the wavelet threshold method, and the greater the noise is, the more obvious the difference of the reconstruction error is.

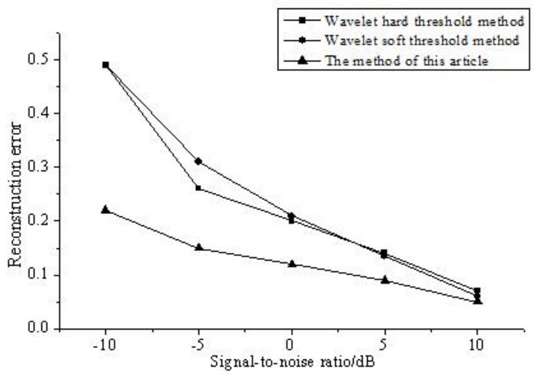

Fig. 3. Comparison diagram of reconstruction error

5. CONCLUSIONS

This research can draw the following conclusions: first of all, the denoising effect of wavelet threshold method decreases with the increase of noise, while the signal filtering method based on K-SVD and OMP algorithm is less affected by noise, and the denoising effect is better than that of wavelet threshold denoising. Secondly, the K-SVD algorithm is used to train the dictionary to get the same structural characteristics as the original signal. Then, the OMP algorithm is used to dilute the signal, and based on the principle that noise cannot be diluted, it can achieve a good denoising effect. Finally, the signal filtering method based on K-SVD and OMP algorithm can not only effectively remove the noise interference in the signal, but also have little influence on the structural characteristics of the original signal, which can better analyze the internal defects of the material, and has a good application prospect.

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