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An artificial bee colony optimization based matching pursuit approach for ultrasonic echo estimation

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ABSTRACT

Ultrasonic echo estimation is important in ultrasonic non-destructive evaluation and material characterization. Matching pursuit is one of the most popular methods for the purpose of estimating ultrasonic echoes. In this paper, an artificial bee colony optimization based matching pursuit approach (ABC-MP) is proposed specifically for ultrasonic signal decomposition by integrating the artificial bee colony algorithm into the matching pursuit method. The optimal atoms are searched from a continuous parameter space over a tailored Gabor dictionary in ABC-MP instead of a discrete parameter space in matching pursuit. As a result, echoes characterized by a set of physical parameters can be estimated accurately and efficiently. The performance of ABC-MP is tested using both simulated signals and real ultrasonic signals, and compared with matching pursuit. Results clearly demonstrate the superior performance of the proposed ABC-MP approach over matching pursuit in ultrasonic echo estimation in terms of the shape and amplitude of the recovered echoes and the reconstructed signal, and the residue signal.

1. Introduction

1.1. Modelling of ultrasonic signals

Ultrasonic inspection is one of the most widely used techniques for non-destructive evaluation (NDE) of materials, and its applications in industries range from defect detection, structural health monitoring, and measurement of material properties. In ultrasonic NDE, an ultrasonic transducer sends pulses and receives reflected echoes from discontinuities in the test sample. According to the acoustic propagation theory, a reflected ultrasonic echo $s(t)$ from a flat surface reflector in pulse-echo mode ultrasonic inspection is often modelled approximately [1] as

$$s(t) = cexp(-B_\alpha(t-\tau)^2)\cos(2\pi f_c(t-\tau)+\varphi) \quad (1)$$

Let $\theta = [c, B_\alpha, f_c, \tau, \varphi]$ denote the parameter vector. The parameters of this model are closely related to the physical properties of the ultrasonic signal propagating through the material. The amplitude of the echo c is primarily governed by the acoustic impedance values of the materials involved, the attenuation of the original signal, and the size and orientation of the reflector. The parameters B_α and f_c are the bandwidth factor and centre frequency, respectively. These parameters are governed by the transducer frequency characteristics and the propagation path. The time of flight τ is related to location of the reflector as the distance between the transducer and the reflector. The phase of the echo φ accounts for the distance, acoustic impedance, size, and orientation of the reflector. Therefore, ultrasonic echoes reflected from homogeneities or discontinuities in tested samples contain information pertaining to the location, size, and characteristics of defects, along with the material and geometry of the test sample [2].

For pulse-echo mode ultrasonic inspection, a recorded signal y (t) is a superposition of ultrasonic echoes $s_i(t)$ reflected from different interfaces inside the test sample,

$$y(t) = \sum_{i=1}^{m} s_i(t) + \xi(t), \quad (2)$$

where $\xi(t)$ accounts for the noise originating from the measurement system and materials. Eq. (2) can be further expanded as:

$$y(t) = \sum_{i=1}^{m} c_i \varnothing_i(t) + \xi(t), \quad (3)$$

where $\varnothing_i(t)$ is the incident pulse impinged to the i^{th} interface, and c_i are the refection coefficients. Due to the limited interfaces and defects in the test sample, the reflection coefficients c_i are generally

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a sparse distribution. From Eq. (3), it can be seen that ultrasonic echo estimation can be formulated as the problem of blind source separation that separates a set of linear mixtures into a number of unknown source signals, inferring both the reflection coefficients c_i, which can be considered as the virtual ultrasonic sources, and the ultrasonic incident pulses $\phi_i(t)$ from the observed signal $y(t)$.

1.2. Ultrasonic echo estimation via sparse signal representation

From Section 1.1, it can be seen that the accurate detection, location and sizing of defects during ultrasonic inspection are limited by the ability to precisely estimate the information of the reflected echoes contained in the recorded ultrasonic signals, including amplitudes/reflection coefficient, time positions, and shape of the echoes. Therefore, ultrasonic echo estimation is an important issue in ultrasonic NDE. Various signal processing techniques have been developed to tackle this issue, and a review can be found in Ref. [3]. The most appealing method among them is sparse signal representation (SSR), an emerging signal processing technique.

SSR decomposes a signal over an overcomplete dictionary. Assume that a dictionary $D = \{\varnothing_i\}_{i=1}^{L}$ consists of L atoms $\varnothing_i$. The atoms are N-dimensional with unit norm, that is, $\varnothing_i \in R^N$ and $||\varnothing_i||_2 = 1$. $N < L$ so that D is overcomplete. For a given signal $y \in R^N$, the SSR technique is to seek a sparse vector $c \in R^L$ satisfying the relationship:

$$y = Dc + \varepsilon, \tag{4}$$

where ε is an error term. This corresponds to solving the following variational problem: Minimize $||c||_0$ subject to $y = Dc$, where $||\cdot||_0$ is the L^0 -norm, counting the non-zero entries of a vector. Directly solving the sparse decomposition problem is NP-hard. The existing SSR algorithms are commonly developed by simplifying the NP-hard problem as a constrained optimization problem by greedy approximations or by applying L^1-norm or L^p-norm constraints on the decomposition coefficients to find sub-optimal solutions. Many SSR algorithms have been developed in the past two decade, such as matching pursuit (MP) [4], greedy basis pursuit [5], Sparse Bayesian learning (SBL) [6], nonconvex regularization [7], and applications of SSR extend into many fields [8–12].

Comparing Eqs. (3) and (4), it can be seen that ultrasonic echo estimation problem can be addressed by SSR directly. Through the sparse decomposition of an observed signal $y(t)$, both the reflection coefficients c_i and the ultrasonic echoes $\phi_i(t)$ can be estimated. Although under an overcomplete dictionary the decomposition of a signal is underdetermined, recent research shows that in many applications this can offer great advantages compared to the conventional signal processing methods. One is that there is greater flexibility in capturing structure in the data [13]. Instead of a small set of general basis vectors, there is a larger set of more specialized atoms such that relatively few are required to represent any particular signal. The second is super-resolution [14]. We can obtain a resolution of sparse objects that is much higher than that possible with traditional methods. The third is that overcomplete representations increase stability of the representation in response to small perturbations of the signal. The fourth is that the redundant representations have the desired shift invariance property [15]. These advantages of SSR are of benefit to the interpretation of an ultrasonic signal. In the past decade, research on SSR in the community of ultrasonic NDE signal processing has attracted an increasing interest and become a hot research area. In [16], MP was used to extract ultrasonic wave shape features of debris echoes and air bubble echoes, and by utilizing the extracted wave shape features, the debris with different shapes and air bubble are distinguished. In [17], SBL was used to denoise the guided wave signal for damage detection. In [18], SBL was employed to estimate the range of frequency and bandwidth parameters of the flaw echoes for structure noise elimination and flaw detection. In [19], taking the advantages of accurate echo separation and echo estimation, MP was integrated into a conventional acoustic micro imaging system, resulting in a super-resolution imaging method. In [20], MP is implemented by the selection of a coarse set of atoms in a tailored discrete Gabor dictionary and interpolation of the atom parameters to improve the accuracy of ultrasonic echo estimation. A comprehensive review about the existing SSR algorithms and their applications in ultrasonic NDE can be found in our recent paper of Ref. [21]. Among all the SSR algorithms, MP is one of the most popular algorithms used in ultrasonic NDE for ultrasonic echo estimation.

1.3. Problem statement

It has been shown that the behavior of the overcomplete dictionary has a great impact on the performance of the SSR methods [22]. In ultrasonic NDE, an ultrasonic echo is usually a broadband pulse modulated at the centre frequency of the transducer, and is usually modelled as a Gabor function as described in Eq. (1). Therefore, the discrete Gabor dictionary is normally used in SSR of ultrasonic signals.

The real Gabor dictionary is defined by $D_R = \{g_{(\gamma,w)} : (\gamma, w) \in \Gamma \times [0, 2\pi]\}$ [23], where $\gamma = (s, u, v)$. For convenience we use the notation $\beta = (\gamma, w)$. g_β is Gabor atoms:

$$g_\beta = g_{(\gamma,w)} = \frac{K_\gamma}{\sqrt{s}} g\left(\frac{t-u}{s}\right)\cos(vt + w), \tag{5}$$

where: s is the scale of the function, u its translation, v its frequency modulation, window function $g(t)$ is Gaussian function $g(t) = e^{-\pi t^2}$, constant and factor $\frac{K_\gamma}{\sqrt{s}}$ normalizes g_β, and w is the phase of the real Gabor atoms.

In practical applications, signal decomposition is normally performed in the discrete Gabor dictionary $D_\alpha = \{g_\beta : \beta \in \Gamma_\alpha \times [0, 2\pi]\}$, a subset of D_R, where Γ_α is composed of all $\gamma = (a^j, pa^j\Delta u, ka^{-j}\Delta v)$ with $\Delta u = \frac{\Delta v}{2\pi}$ and $\Delta u \cdot \Delta v < 2\pi$, $j \in Z$, $p \in Z$, $k \in Z$ [24]. In the practical sparse decomposition, the parameters $\gamma = (s, u, v)$ are normally discretised as follows:

- $s[j] = a^j$, for $1 \ll j \ll n$ where n is the biggest integer power of a such that $a^n \leqslant N$, where N is the length of the input signal. In many applications, a is set as 2.
- $du[j] = s[j]/2$ and $dv[j] = \pi/s[j]$.
- $u \in \{pdu|p \in Z, 0 \leqslant p, pdu \leqslant n-1\}$.
- $v \in \{kdv|k \in Z, 0 \leqslant k, kdv < rmv\}$, where $rmv = 2\pi$.

It is proven in [23,24] that if the parameters s, u, v are discretised as indicated above the fourth parameter w is uniquely determined in the standard MP algorithm.

In our application, the atoms in the overcomplete dictionary should match the ultrasonic echoes as close as possible in order to obtain accurate echo estimation. In order to achieve this goal, the parameters s, u, v in the real Gabor dictionary D_R is required to be discretised as fine as possible rather than the above partition. In [20], it demonstrated that refining the parameters significantly improves the performance of MP.

However, for given parameter bounds, this means significantly increase the size of the discrete Gabor dictionary D_α. According to the SSR theory, MP finds the optimal solution only when the dictionary size, i.e., the number of atoms in the dictionary, is smaller than a threshold due to cumulative coherence bound [22].