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Best basis compressive sensing of guided waves in structural health monitoring

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ABSTRACT

A novel signal compression and reconstruction procedure suitable for guided wave based structural health monitoring (SHM) applications is presented. The proposed approach combines the wavelet packet transform and frequency warping to generate a sparse decomposition of the acquired dispersive signal. The sparsity of the signal in the considered representation is exploited to develop data compression strategy based on the Best-Basis Compressive sensing (CS) theory. The proposed data compression strategy has been compared with the transform encoder based on the Embedded Zerotree (EZT), a well known data compression algorithm. These approaches are tested on experimental Lamb wave signals obtained by acquiring acoustic emissions in a 1 m^2 aluminum plate with conventional piezoelectric sensors. The performances of the two methods are analyzed by varying the compression ratio in the range 40–80%, and measuring the discrepancy between the original and the reconstructed signal. Results show the improvement in signal reconstruction with the use of the modified CS framework with respect to transform-encoders such as the EZT algorithm with Huffman coding.

1. Introduction

Guided waves (GW) based approaches are an attractive mean for monitoring many important structural components in aerospace systems, land and marine transportation, civil infrastructures, and in the oil and gas industry [1]. In fact, approaches based on GW allow the inspection of large areas and provides excellent sensitivity to multiple types of damage [2,3]. Such capabilities have been widely exploited for instance in GW based methodologies for impact/damage localization in plate-like structures.

In such applications, generally arrays of piezoelectric transducers are used to record acoustic emissions. Several array shapes have been investigated, including single-ring or fully populated circular patterns [4], two-dimensional square arrays [5] or more complicated configurations realized with piezoelectric paint [6]. The typical mode of operation of these systems involves the phased actuation of transducers and the observation of several dynamic response measurements from large network of sensors. While the majority of sensor networks in use today employs a wired architecture, development of wireless sensor networks has exploded in recent years [7].

The integration of wireless communication technologies into SHM methods has to be investigated since they eliminate the cost of cable deployment and reliability issues due to aging and debonding of cables of traditional SHM systems, and have distinct advantages such as simple, cost-effective, flexible, and reconfigurable, thus allowing scalable installation [8].

However, in embedded sensing devices, the wireless connectivity may consume a large fraction of the available energy. Therefore, in order to achieve long battery lifetime, performing data reduction *locally*, i.e. within the wireless smart sensors, is of primary importance [9,10]. By doing so communication traffic can be greatly reduced, minimizing the need of storing or transmitting large amount of multichannel data. Data reduction could consist either in the extraction of relevant information (such as time of flight or energy [11,12]) from the acquired waveform, or in signal compression. When the information extraction task is too much computationally onerous to be performed on a local embedded processor, the best option is to compress efficiently the acquired signal, and then to transmit it to a central unit where the signal is recovered and the processing is performed [13,14].

In this work, a signal compression strategy specifically dedicated to Lamb wave signals for SHM, and aimed at achieving high

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compression ratio with low distortion in signal recovery is proposed. For signal compression, a novel approach is proposed whose starting point is the design of a suitable signal representation basis. The framework rely on the assumption that Lamb wave signals can be sparsified in a frequency warped domain [15]. The warping procedure allows to design a time–frequency decomposition matched to the dispersive behavior of Lamb waves, i.e. achieving a sparse representation of the signal; further improvement in the sparsity of the signal can be obtained with a proper basis designed by reshaping the scale domain through the warped Wavelet Packet (WP) decomposition [16,17]. In this article we use a dictionary of warped wavelets, adaptively selected in the warped wavelet packet decomposition tree by means of the Best Basis algorithm, to achieve maximally sparse representations. Moreover we have analyzed and studied the wavelet filter banks design to compute the adaptive warped wavelet basis.

The proposed dictionary selection procedure has been exploited within a Compressive sensing (CS) framework [18] through the minimization of a surrogate cost function and it has been compared with a well-known data compression scheme, i.e. the Embedded Zerotree (EZT) coding [19]. Both the approaches rely on the assumption that Lamb wave signals can be represented as sparse linear combination of basis functions.

The structure of this paper is as follows: in Section 2 the Wavelet Packet transform and the Best Basis parametrical optimization is presented, while Section 3 is devoted to the data compression procedures: the Embedded Zerotree WP encoding is presented in Section 3.1, and the CS procedure with the Best Basis WP is described in Section 3.2. The proposed CS framework that exploits the Frequency Warped basis is detailed in Section 4. Experimental validations of the proposed CS framework and the comparison with the EZT coding are shown in Section 5. The experiments consist in compressing and recovering dispersive guided wave signals acquired in an aluminum plate by using PZT sensors. The conclusions end the work.

2. Parametrized discrete wavelet packet transform

Multiscale transformations such as the wavelet transform (WT) analyze and represent efficiently ultrasonic [20,21,15,12] or electrocardiogram signals [22]. Let us call $x \in \mathbb{R}^N$ the real-valued vector which may represent the discretized guided Lamb wave signal, in the considered application domain. The WT operator $\boldsymbol{\Psi}$ can be used to decompose the signal x such that $x = \boldsymbol{\Psi}\alpha$, where α is the N-dimensional WT coefficients vector.

The signal is said to be *sparse* in the new representation basis, if the vast majority of the entries of $\theta = [\theta_1, \theta_2, \ldots, \theta_N]$, are zero-valued or negligible. Sparse signals can be approximated using just the K largest entries of θ and setting all other terms to zero:

$$x \approx \sum_{k=1}^{K} \theta(k)\psi(k), \quad \text{with} \quad K \ll N \tag{1}$$

where the functions $\psi(k)$ are elements of the wavelet basis.

As for the WT, the inner products between the signal and the elements of the adjoint operator $\boldsymbol{\Psi}^\dagger$ which produce the wavelet coefficients can be computed efficiently by applying nested low-pass h and high-pass g filters to the original signal x as suggested by the Multiresolution Analysis theory developed by Mallat [23]. Depending on the sequence (tree) of the low and high pass filters, different wavelet transforms take place.

As known, the frequency resolution which can be achieved by using an octave-band finite impulse response (FIR) filter is limited, especially at high frequencies. This limits the use of the Discrete Wavelet Transform (DWT) in guided waves based applications.

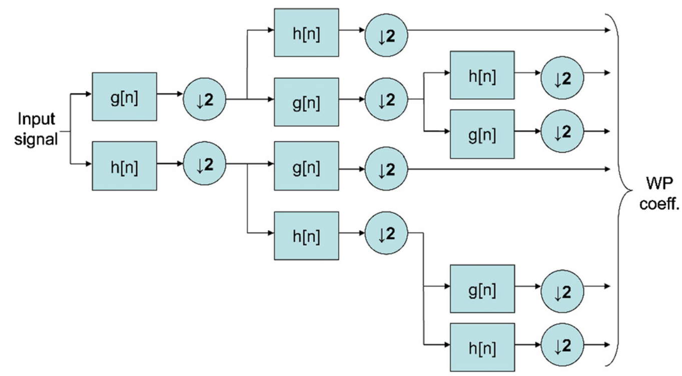

Fig. 1. Pruned (Best Basis) Wavelet Packet decomposition.

The Wavelet Packet (WP) transform is a generalization of the DWT decomposition where the outputs of the filters h, the signal approximations, and also the outputs of the filters g, the details, are filtered while stepping in the next decomposition level.

Alternatively, the number of filtering stages of the full WP tree can be limited (*pruning*) by selecting the decomposition depending on the signal characteristics, as schematically represented in the example in Fig. 1.

As for guided Lamb wave signals, a suitable pruning allows to obtain a discrete representation of the signal better matched to its inherent multi-scale structure.

To such aim, in this work a procedure that couples the pruning (*Best-Basis*) technique [24] with the lattice parametrization of the wavelet basis [25] is proposed. More specifically, the wavelet basis is defined by a proper parametrization of the coefficients of the scaling filter h. For a finite impulse response filter of length L, there are $L/2+1$ conditions to ensure that the wavelets define an orthogonal Discrete Wavelet Packet Transform (DWPT) and thus there are $L/2-1$ degrees-of-freedom to design the scaling filter h. The lattice parametrization presented in [25] offers the opportunity to design orthogonal wavelet filters via unconstrained parameters.

In particular, for $L=6$ the design parameters α and β gives

$$i=0,1 : h[i] = \frac{1}{4\sqrt{2}} \times [(1+(-1)^i\cos\alpha + \sin\alpha) \times (1-(-1)^i\cos\beta - \sin\beta) + (-1)^i 2\sin\beta\cos\alpha]$$

$$i=2,3 : h[i] = \frac{1}{2\sqrt{2}} \times [(1+\cos(\alpha-\beta) + \sin\alpha + (-1)^i\sin(\alpha-\beta))]$$

$$i=4,5 : h[i] = \frac{1}{\sqrt{2}} - h(i-4) - h(i-2)$$

The optimal parameters are chosen to minimize the distortion of the signal after decoding for a given compression rate, in the case of signal compression. The metric used to quantify the difference between the original signal $x[n]$ and the reconstructed signal $\hat{x}[n]$ after decoding is the percent residual difference (PRD) (%)

$$PRD = \sqrt{\frac{\sum_n (x[n]-\hat{x}[n])^2}{\sum_n x[n]^2}} \times 100 \tag{2}$$

In other words, the selected decomposition is optimal in the sense that corresponds to a time frequency tiling that best concentrates the Lamb wave signal energy in few WP coefficients.