Optimal Compression of Vibration Data with Lifting Wavelet Transform and Context-based Arithmetic Coding

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***Abstract*—This paper proposes an adaptive vibration signal compression scheme composed of a lifting discrete wavelet transform (LDWT) with set-partitioning embedded blocks (SPECK) that efficiently sorts the wavelet coefficients by significance. The output of the SPECK module is input to an optimized context-based arithmetic coder that generates the compressed bitstream. The algorithm is deployed as part of a reliable and effective health monitoring technology for machines and civil constructions (e.g. power generation system). This application area relies on the collection of large quantities of high quality vibration sensor data that needs to be compressed before storing and transmission. Experimental results indicate that the proposed method outperforms state-of-the-art coders, while retaining the characteristics in the compressed vibration signals to ensure accurate event analysis. For the same quality level, up to 59.41% bitrate reduction is achieved by the proposed method compared to JPEG2000.**

I. Introduction and Motivation

Failures in machine structural integrity can be a significant contributor to increased running costs, unplanned outages and even catastrophic failures of machines and civil constructions (e.g. power generation plant). The stringent safety considerations together with the cost of such outages makes essential the effective Condition Monitoring (CM) of all machinery vital to plant operation. To achieve this, continuous streams of raw noise and vibration data are routinely captured by CM systems. However, storage of data is costly, and transfer from the sensor to the control room depends on the availability of a high bandwidth network. This is currently addressed by applying algorithms that produce low bandwidth Condition Indicators (CI) in the process discarding raw data. However, the understanding of failures resulting from transient events is more difficult if the reduced sampling frequency means that valuable information is lost. The development of a data compression system that can automatically adapt its acquisition conditions and compress the vibration signal at source without loss of critical information represents a significant benefit for the machinery industry, allowing future CM solutions to replay what happened. The availability of reliable monitoring data leading up to and during an event, enables robust decision making.

This paper presents a novel vibration sensor data compression system based on lifting wavelet transforms in conjunction with a wavelet coefficient sorting algorithm, followed by context-based arithmetic coding. The main contributions of this paper are:

1) We propose a lifting-based discrete wavelet transform (LDWT) integrated with the SPECK algorithm for efficiently sorting the wavelet coefficients of the vibration sensor signal.
2) We propose a novel context model for the SPECK algorithm in order to minimize the number of coding coefficients. A context-based arithmetic coder is utilized to compress the vibration signal efficiently. This is the first time to our knowledge that the SPECK algorithm is extended with arithmetic coding and novel context-based modeling applied to difficult to compress and noisy vibration data.
3) We perform an extensive evaluation of the proposed method with additional test material and coding conditions suitable for different types of vibration sensor data. The evaluation contains 6840 coding conditions which including 38 vibration signals, 5 different bit-depths representations, 4 thresholds and comparisons with 9 encoding methods.

The remainder of this paper is structured as follows. Section 2 gives an overview of the related work in data compression. Section 3 presents the proposed vibration sensor data compression system, while Section 4 presents performance results and comparisons with different methods. Finally, Section 5 concludes this paper and suggests potential future work.

II. Related work

To achieve vibration sensor data compression, several studies in the area of remote conditioning monitoring have focused on bearing vibration signals with lossy and lossless compression schemes. Some of those approaches rely on transform based methods, mostly using various discrete cosine transform (DCT) and discrete wavelet transform (DWT) [1], [2], [3], [4]. The suitability of transform methods for the compression of signals with non-stationary characteristics is well known [1], [5], [6]. Shapiro proposed a wavelet-based image entropy coder Embedded Zerotree Wavelet (EZW) in [7]. Two key concepts developed in the EZW are: significance map coding with zerotrees and successive approximation quantization. The Set Partitioning in Hierarchical Trees (SPIHT) algorithm has

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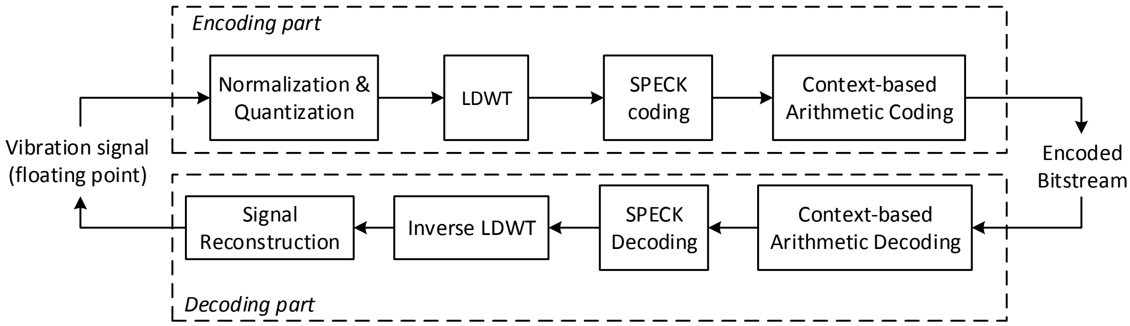

Fig. 1: Overview of proposed vibration signal compression system.

been proposed in [8] and offers an improvement over EZW. The key point of this improvement is that in SPIHT, a rule is used to split sets (that are represented as nodes in a tree) into subsets (the descendant nodes of the split set) depending on their significance (the amplitude of wavelet coefficients). The SPECK algorithm has been proposed in [9], which is the evolution of the SPIHT. The difference between SPECK and SPIHT is that, SPECK does not use trees and spatial structure which span and exploit the similarity across different subbands of a wavelet decomposition; instead, it makes use of sets in the form of blocks of contiguous coefficients within subbands to exploit the clustering of energy in frequency and space in hierarchical structures of the transformed signal. In [10], a modified low-memory implementation of SPECK algorithm (ZM-SPECK) has proposed for quantization and coding of the DWT coefficients. The proposed method completely eliminates the linked lists and only use registers to perform low-level arithmetic/logical operations. This implementation reduces the memory required at the transfer and coding stage with low-complexity encoding in sensor nodes. State-of-the-art image and video coding standard such as JPEG2000 [11] and the HEVC reference software Model (HM) codec [12] also employ transform-based and predictive coding. In this research, JPEG2000 has been employed as a benchmark during the evaluation phase.

In this work the SPECK algorithm is selected due to its good properties handling non-stationary signals. Its performance is improved with a lifting-based DWT and context-based arithmetic coding. Unlike previous work that indicates that arithmetic coding applied to SPECK offers modest improvements [9], [11], the proposed context-based technique delivers significant compression gains.

III. Proposed LDWT-SPECK based compression system with context modeling

Figure 1 shows an overview of the system which consists of the following components:

A. *LDWT-SPECK based compression system*

The benefit of the wavelet transform in data compression is that it is capable of decomposing a complex signal into its basis signals of finite bandwidth. Traditional wavelet transform such as Discrete Wavelet Transform (DWT) use high- and low-pass analysis filter banks on the input signal for forward DWT, and synthesis filter bank for signal reconstruction. The main feature of the lifting-based DWT (LDWT) is that it breaks up the analysis and synthesis filters into a sequence of upper and lower triangular matrices, and converts the filter implementation into banded matrix multiplications [13]. The block diagram of the lifting scheme is illustrated in Figure 2. The lifting based forward wavelet transform applies the *lazy* wavelet on the even (x_e) and odd (x_o) samples of input signal (x), then it applies *prediction* (P) and *update* (U) lifting steps, and finally scales the two output streams by a scaling factor, to produce low- (l) and high-pass (h) subbands. The inverse transform can be derived with the reversed steps. Due to the linearity of the lifting scheme, it is capable of transforming signals losslessly when it is used with an integer number representation and in this case it is called Integer Wavelet Transform (IWT) [14]. The advantages of the lifting scheme are listed below:

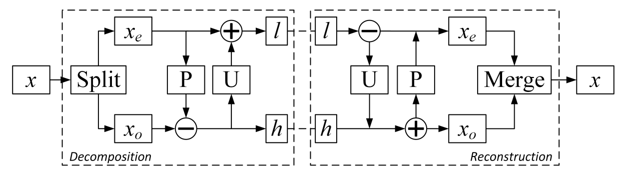

Fig. 2: Illustration of lifting wavelet decomposition and reconstruction.

- Lifting allows for adaptive wavelet transform.
- The LDWT allows lossless reversible integer-to-integer transform.
- Lifting allows fast forward and inverse wavelet transforms and a simple implementation.

For these reasons, the LDWT is employed for the multi-resolution time-frequency domain analysis of the vibration signal in the compression system proposed in this paper. The lifting scheme enables an adaptive wavelet transform, which means that the transform can start analysis of a function from the most important (fundamental) layers and then build the detail layers by refining only the areas of interest. In the decoding part, the decoder can adaptively refine the detail information based on the requirements. An efficient wavelet

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coefficient sorting algorithm such as SPECK is helpful to sort subsets of wavelet coefficients by significance.

SPECK uses three dynamic lists to store significant information of wavelet coefficients for compression purposes, which are the list of significant pixels (LSP), list of insignificant pixels (LIP) and list of insignificant sets (LIS). To check the significance, the algorithm compares the wavelet coefficients in a set with respect to a sequence of decreasing threshold. In case that the wavelet coefficient has its magnitude above the threshold, the set is split into four subsets whose significance with respect to the threshold is tested, otherwise, the set is not split. At the end, the algorithm rescans those pixels found to be significant with respect to previous thresholds, and refines their magnitude. The function used for testing the set significant state is defined by the following formula:

$$S_n(\Gamma) = \begin{cases} 1, & 2^n \leq \max\limits_{(i,j)\in\Gamma} \{|c_{i,j}|\} \leq 2^{n+1} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$n = \left\lfloor \log_2(\max_{(i,j)} \{|c_{i,j}|\}) \right\rfloor \tag{2}$$

where $c_{i,j}$ is the coefficient value for (i,j) position in the wavelet subbands. The Γ indicates the set of coefficients and $S_n(\Gamma)$ is used for significant state of the set Γ, where 1 indicates the set is significant to the threshold $T = 2^n$, and 0 indicates it is insignificant and a bit will be emitted for the entire insignificant set. The insignificant pixels and insignificant sets are put in LIP and LIS, respectively; the significant pixels are put in the LSP. The general idea of the SPECK algorithm follows the SPIHT [8]. The difference lies in the sorting pass where the set of type *S* as defined above has been used, instead of using spatial orientation trees for significance testing. The algorithm exploits the clustering of energy found in the transformed domain and concentrated on those areas of the set which have high energy. This allows those signals with higher information to be encoded first based on their energy content. In this work the pixels are the samples present in the vibration signal so the same approach can be used.

B. Context modeling for arithmetic coding in SPECK

Arithmetic coding (AC) can obtain optimal performance thanks to its ability to represent information with fractional bits. AC has been widely utilized by various image and video codecs, such as the QM coder in JPEG [15], the MQ coder in JPEG2000 [16], and the context-based adaptive binary arithmetic coder (CABAC) in H.264/AVC and HEVC [12].

The context modeling provides estimates of the conditional probabilities of the coding coefficients and exploits the redundancy present in the neighborhood of the current coefficient to encode. In our proposed vibration data compression system, the context modeling of a current coefficient, $C_{i,j}$, at (i,j) position in SPECK is defined based upon the significance of the current coefficient and its neighbors, as shown in Figure 3, where C^{sign} (where sign $\in (h, v, d)$), represents the horizontal, vertical and diagonal coefficients respectively. The context number $\kappa^{\text{sign}}(i,j)$ of the current coefficient is formed from three intermediate quantities,

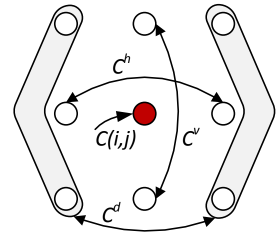


Fig. 3: Formation of coding context modeling.

TABLE I: Proposed context modeling for significance coding

$\kappa^{sign(i,j)}$	LL and LH subbands			HL subbands			HH subbands	
	κ^h	κ^v	κ^d	κ^h	κ^v	κ^d	$\kappa^h + \kappa^v$	κ^d
8	2	$\times$	$\times$	$\times$	2	$\times$	$\times$	≥ 3
7	1	≥ 1	$\times$	≥ 1	1	$\times$	≥ 1	2
6	1	0	≥ 1	0	1	≥ 1	0	2
5	1	0	0	0	1	0	≥ 2	1
4	0	2	$\times$	2	0	$\times$	1	1
3	0	1	$\times$	1	0	$\times$	0	1
2	0	0	≥ 2	0	0	≥ 2	≥ 2	0
1	0	0	1	0	0	1	1	0
0	0	0	0	0	0	0	0	0

$$\begin{aligned} \kappa^h(i,j) &= \sigma(i,\ j-1) + \sigma(i,\ j+1), \\ \kappa^v(i,j) &= \sigma(i-1,\ j) + \sigma(i+1,\ j), \\ \kappa^d(i,j) &= \sum_{x=\pm 1} \sum_{y=\pm 1} \sigma(i+x,\ j+y) \end{aligned} \tag{3}$$

where σ represents the significance of the $C(i,j)$, $\sigma = 1$ represents a coefficient that is currently significant, otherwise, $\sigma = 0$. Table I shows the proposed context modeling of significance coding for SPECK optimized for vibration data in different wavelet subbands. For instance, in the HL subband, the significant coefficients are most likely to arise from vertically oriented features in the constructed 2D array. Thus, the significance of vertical neighbors is considered most indicative of the current coefficients significance. The horizontal neighbors are considered as the second most important indicators of the significance of the $C(i,j)$. The diagonal coefficients are considered only if none of the κ^h and κ^d are significant.

The arithmetic coder employed in this work is the MQ-coder as specified in the JBIG and JPEG2000 standard [11], [16]. The MQ-coder is a binary alphabet adaptive multiplication-free arithmetic coder. A probability model has been implemented as a 47-state Finite State Machine (FSM) for the coding process. In the FSM, each state contains coding information, a set of probability mapping rules (look-up table) which are used to interpret and manipulate the context state associated with the current coding context [11]. It can estimate the probability of the context more efficiently, and take into consideration the non-stationary characteristic of the symbol string. The MQ-coder can adapt to the input bit stream by estimating the probability through the use of two tables: *Dynamic table* and *Static table*. The *Dynamic table* contains the information of each context, and the *Static table* describes the probability state transition for MQ-coder [11].

IV. Experimental results and Discussion

We have compressed a total of 38 vibration signals where 29 signals are collected from machines located at an operative nuclear power station. 9 signals are from public datasets [1], including "*CarVibII*", "*SuspensioBridge*", and "*WardLeonard_DCGenerator*", each of these contains three signal channels. The vibration signals were compressed by the proposed coding framework and compare with 6 additional coding methods.

We consider that data organized as a 2D matrix since initial results show that the 2D format can exploit additional correlations present in signals that show periodic features. Since these periods are not easy to determine in the general case in these experiments the 2D matrices were simply obtained by splitting the 1D signal by 2^n samples width with 2^n height, where $n = 8$ in this research.

To evaluate the performance of the data compression approaches reliably, two critical issues need to be considered: the compression ratio (CR) and the distortion measure as the signal to noise ratio (SNR) of the reconstructed signal compared to the original signal, as shown in (4) and (5).

$$\mathrm{CR} = \frac{L_{\mathrm{orig}}}{L_{\mathrm{comp}}} \tag{4}$$

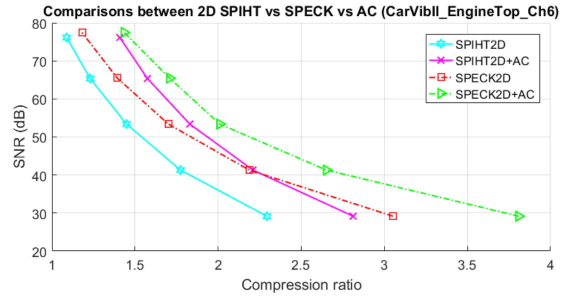
where L_{orig} and L_{comp} are the bits of the original signal and compressed signal, respectively.

$$\mathrm{SNR} = 10 \cdot \log_{10} \frac{\sum_{i=1}^{N} |s(i)|^2}{\sum_{i=1}^{N} |s(i) - \hat{s}(i)|^2} \tag{5}$$

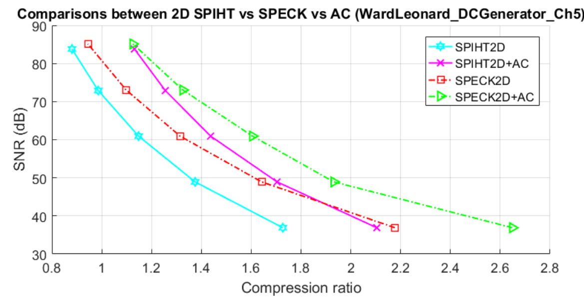
where $s(i)$ and $\hat{s}(i)$ are the original signal and reconstructed signal, respectively.

Figure 4 shows four sets of experimental results. The figures demonstrate the performance of the algorithm versions developed based on 2D-SPIHT and SPECK algorithms with and without AC on *CarVibII*, *WardLeonard_DCGenerator*, *SuspensionBridge* and *Main_Turbine* signal. The experimental results indicated that the 2D-SPECK provides better compression performance than SPIHT. With the aid of AC, the 2D-SPECK AC provides even better performance compare with 2D-SPIHT AC. Based on these results, we select 2D-SPECK algorithm for further evaluations.

Figure 5 shows four sets of experimental results which are obtained with the same vibration sensor data as used in Figure 4. The figures demonstrate the performance of the 2D-SPECK AC, JPEG2000 and a version of 2D-SPECK AC that deploys the optimized context modeling strategy for the arithmetic coding discussed in Section 2. We use the compression ratio parameter of JPEG2000 to reduce the compressed data to a desired CR and SNR value. To assess the performance benefit brought by the proposed method, the compression ratio achieved has been measured at the same level of quality of the reconstructed signal, as indicated by the SNR metric, as shown in Figure 5. The experimental results indicate that the proposed LDWT-based 2D-SPECK in conjunction with optimized context modeling for CBAC constantly produces better rate-distortion performance compared to JPEG2000 and 2D-SPECK AC. This is especially noticeable in higher SNR values which offer the best reconstruction quality important in



(a)



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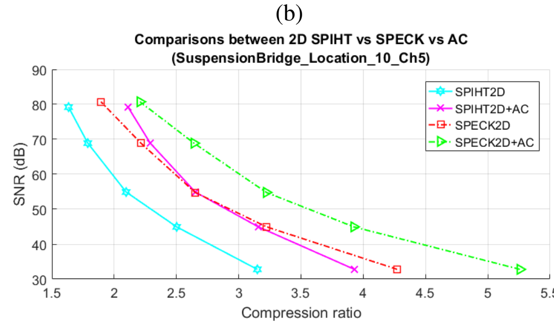

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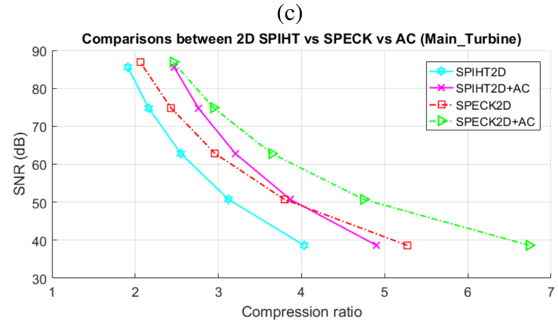

(d)

Fig. 4: Performance of the 2D SPIHT and SPECK algorithm with / without AC on (a) *CarVibII*, (b) *WardLeonard_DCGenerator*, (c) *SuspensionBridge* and (d) *Main_Turbine* test signals.

[1]The dataset available from: http://eh-network.org/data/

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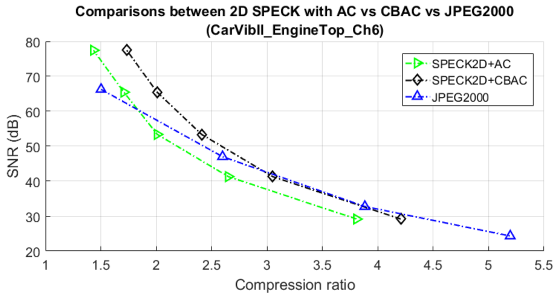
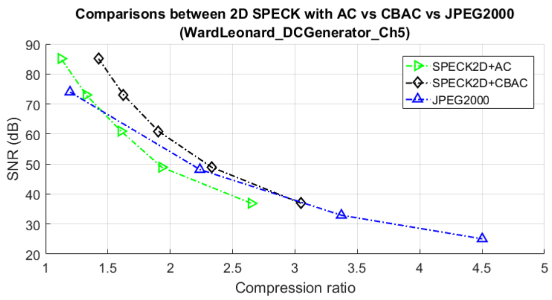


(a)



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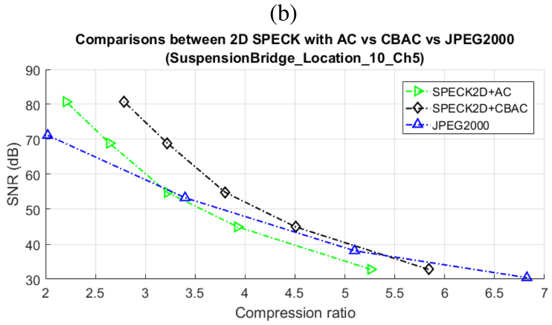
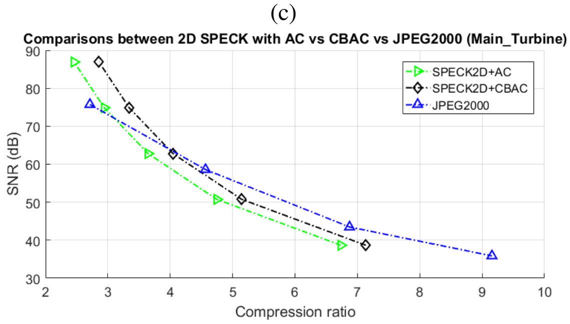


(c)



(d)

Fig. 5: Performance of the 2D SPIHT and SPECK algorithm with / without AC on (a) *CarVibII*, (b) *WardLeonard_DCGenerator*, (c) *SuspensionBridge* and (d) *Main_Turbine* test signals.

machine monitoring. Overall, the proposed method improves the CR of the coded bit stream by 28.85% on average for all 38 test vibration sensor signals. Up to 33.8% (SNR = 66.27dB), 35.95% (SNR = 73.98dB), 59.41% (SNR = 71.13dB), and 23.32% (SNR = 75.73dB) improvement in CR was obtained with the *CarVibII*, *WardLeonard_DCGenerator*, *SuspensionBridge* and *Main_Turbine* signal respectively.

V. Conclusion

In this paper, an efficient high quality vibration sensor data compression system is proposed which outperforms existing state-of-the-art codecs, such as JPEG2000. The proposed method employs the LDWT with SPECK sorting algorithm to increase the coding performance by reducing the number of coefficients that needs to be coded, as well as exploiting the higher order statistical dependencies with context-based modeling and arithmetic coding. Experimental results indicate that the proposed method offers a significant improvement in CR with the same quality across all 38 testing vibration sensor signal, measured objectively using the SNR metric. In future work, we intend to test the proposed method exploring correlations across different signal channels extracted from the same machine. In addition, the computational complexity and statistical characteristics of the signal influencing compression performance will be investigated.

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