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RESEARCH ARTICLE

Improvement of the compression ratio of vibratory signals by double pass DWHT

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Abstract

Background/Objectives: The vibratory signals delivered by rotating machines are very important in the maintenance of these machines. For maintenance purposes they are stored or transmitted. The storage and transmission of these signals pose problems of space and bandwidth. To solve this problem compression is a solution. **Methods/Statistical analysis:** In this work, we compress and decompress the vibration signals formed by variations of the amplitudes vibration of a ball bearing. We used an algorithm based on the Walsh-Hadamard Transform (WHT) in two passes. The coefficients obtained are coded according to Huffman's coding. An evaluation of performances of this algorithm is made on the basis of the measurements of SNR, MFD, MSE, PRD and CR. **Findings**: Compression ratios are high when we consider that the reconstruction is almost perfect. Usually, compression methods by transformation have a nonzero reconstructed error. However, this bleaching of vibratory signals both in the temporal and frequency domain, followed by good quantization precision, allowed to cancel this error. In view of these qualitative and quantitative evaluation parameters of the method result, it can be said that the method gives very good results. **Novelty/Applications:** Improved of Compression Ratio of vibratory signals for maintenance purposes.

Keywords: WHT; compression; vibratory signals; storage; bandwidth; rotating machines

1 Introduction

The monitoring of rotating machines by vibratory analysis has become a topic of great importance in recent years. Initially, it was intended to protect the installations from mass damage and even accidents at work. Vibration analysis is an important means of predicting malfunctions in moving systems. This prediction involves the production of data that informs the operating state of the system. These data are heavy and therefore occupy a lot of storage space[(1)].

The objective of our work is to improve the compression ratio of vibratory signals resulting from the functioning of a ball bearing. The information targeted during the acquisition are the vibration amplitude.

Several signals have been compressed to facilitate their storage and/or transmission. Thereby, Amanjot and Jaspreet compressed the images to compare two compression techniques: the Discrete Cosines Transform (DCT) and the Discrete Wavelets Transform (DWT). This study showed that, despite the fact that the qualitative and quantitative compression parameters are very close for the two algorithms, the computational load of the DCT is higher than that of the DWT[2]. Habchi Yassine et al., compressed biomedical images using DWT. The aim of this study was to improve the visual quality of biomedical images at decompression[3]. Rohit Kumar et al., compressed multimedia images with fuzzy logic followed by Huffman coding. This work aimed the improving capacities of the storage of these informations[4]. Aviv Barabi et al., recorded and compressed images resulting from an endoscopy exploration, with the aim of facilitating their wireless transmission[5]. Premanand and Sheeba compressed vibration signals by using extremum sampling method, this method is based on level-crossing sampling[6]. Xiao Chaoang et al. presented a novel method of compressed sensing reconstruction for axial piston pump bearing vibration signals based on the adaptive sparse dictionary model[7]. Narayan et al. explored the potential relationship between various combustion events monitored using in-cylinder pressure transducer and the resulting block vibration measured using accelerometers[8]. Jaafar Kh Alsalaet et al. proposed a compression scheme based on Modified Discrete Cosine Transform (MDCT) algorithm to compress vibration signals[9]. Jiedi Sun et al. proposed a compressed data acquisition and reconstruction scheme based on Compressed Sensing which is a novel signal-processing technique and applied it for bearing conditions monitoring via WSN[10].

In the literature several works on the maintenance of rotating systems in general and on vibratory signals in particular have been the subject of many publications. Some authors use mathematical models to solve maintenance problems. Thereby, Bazovsky introduced the use of mathematical optimization methods in preventive maintenance policies[11]. Jardine introduced decision models for the determination of revision intervals through reliability and cost analysis[12]. Other authors use space change to detect malfunctions. For example, Cavacece et al. used the power spectrum to detect defects at an early stage in aeronautical transmissions[13]. Minnicino et al., used Hilbert transform to detect and diagnose rotating machine defects[14]. Pusey and Roemeront gave an overview of the development of diagnosis and prognosis in high-performance technologies on turbomachinery[15]. Jardine et al., provided an overview and catalogue of publications on data acquisition and processing, diagnosis and prognosis of different machines[16]. Basile has developed a statistical approach to establish a law of reliability for equipment. This approach is based on feedback[17]. Vachtsevanos et al., defined and described fault diagnosis by the Artificial intelligence method and approaches to failure prediction by systems engineering through examples[18]. Despite the fact that several types of signals have been compressed for different purposes, the compression algorithm that uses the DWHT in multi-pas was not tested on the vibratory signals. The originality of this work lies in the improvement of the compression ratios of vibratory signals by using the Walsh-Hadamard transform in multi-pass mode.

This article consists of three parts: the state of the art, methodology, analysis and interpretation of the results.

2 Materials and Methods

The method presented in this article was implemented on a real vibratory signal made of 256 samples. This signal is a recording of the vibration monitoring of a ball bearing. The reference of this bearing is SKF7309B. The acquisition system consists of a portable collector, VIBROTEST 60 and an accelerometer. The signals were acquired with a sampling frequency of 2 kHz. The acquisition device model uses a A/N converter 12-bit. The vibration parameter chosen for this work is amplitude variation.

2.1 Generalities on compression

The goal of compression has always been to reduce the size of the data while maintaining a better quality of the reconstructed signals. There are two types of compression, lossless compression and lossy compression. In lossless compression, decoded information is the perfect image of the original information. A restraint of this method is the low compression ratio[19]. Conversely, lossy compression offers high compression rates but at the expense of reconstructed data quality[20]. The general diagram of compression/decompression follows the principle of Figure 1.

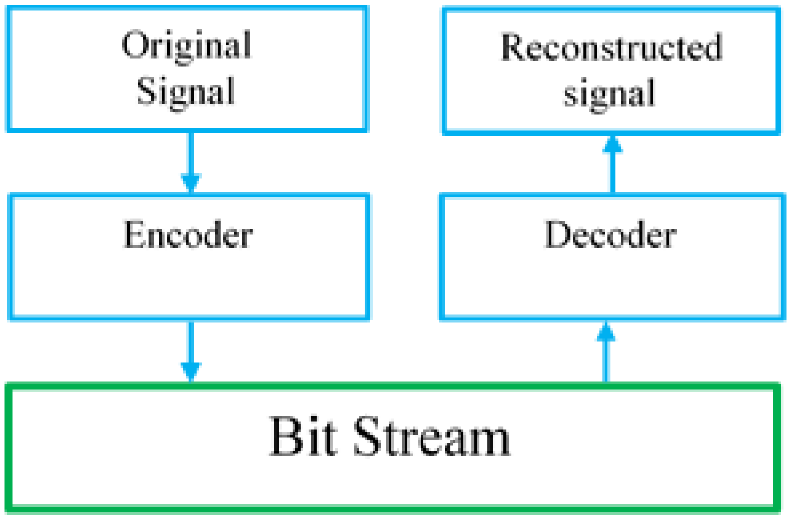

Fig 1. Compression/decompression chain

Figure 1 shows the general data compression/decompression procedure. The original signal is processed by the encoder. In the case of lossless compression, the original signal is simply encoded and at its output a binary train is obtained. In the case of lossy compression, the original signal is decorrelated in the encoder often by an orthogonal transformation. The coefficients obtained are quantified and coded. At the output of the encoder we obtain a binary train. The decompression follows this algorithm but in the opposite direction. Diverse orthogonal transformations were used for data compression (DWT, DCT, KLT and WHT)[21,22]. This use is motivated by capacites of these transformations to compact and to bleach data[23].

2.2 Compression Evaluation Parameters

Several parameters are used to evaluate the quality of a compression. One of these parameters is the compression ratio. It defines the capacity of a compression algorithm to reduce data size. Its expression is specified by equation (2.1).

$$RC = \left(1 - \left(\frac{size\ of\ compressed\ file}{size\ of\ original\ file}\right)\right).100\% \tag{2.1}$$

To evaluate a lossy compression method, it is often necessary to associate the compression ratio with other parameters for a qualitative evaluation of the algorithm. For that, Four quality parameters are used.

Mean Squared Error (MSE),

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(s_0(n) - s_r(n)\right)^2 \tag{2.2}$$

$s_0(n)$ is the original signal ;

$s_r(n)$ is the reconstructed signal ;

N is the number of signal samples

Signal to Noise Ratio (SNR)

$$SNR = 10log\left(\frac{\sigma_x^2}{\sigma_e^2}\right) \tag{2.3}$$

With σ_x^2 representing the power of the original signal and σ_e^2 representing the power of the error.

Mean Frequency Distorsion (MFD),

$$MFD = \left(\frac{|F_{orig} - F_{recons}|}{max\left(F_{orig},\ F_{recons}\right)} \right)^2 \tag{2.4}$$

In formula (4), Forig and Frecons represent the average frequency calculated respectively on the original signal and on the reconstructed signal.

Percent Root mean square Difference (PRD)

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1}\left(s_0\left(n\right) - s_r(n)\right)^2}{\sum_{n=0}^{N-1}\left(s_0\left(n\right) - \mu\right)^2}}.100\% \tag{2.5}$$

μIs the reference value of the CAN used for data acquisition s(n).

2.3 Proposed method

The compression/decompression scheme implemented in our algorithm is given in Figure 2.

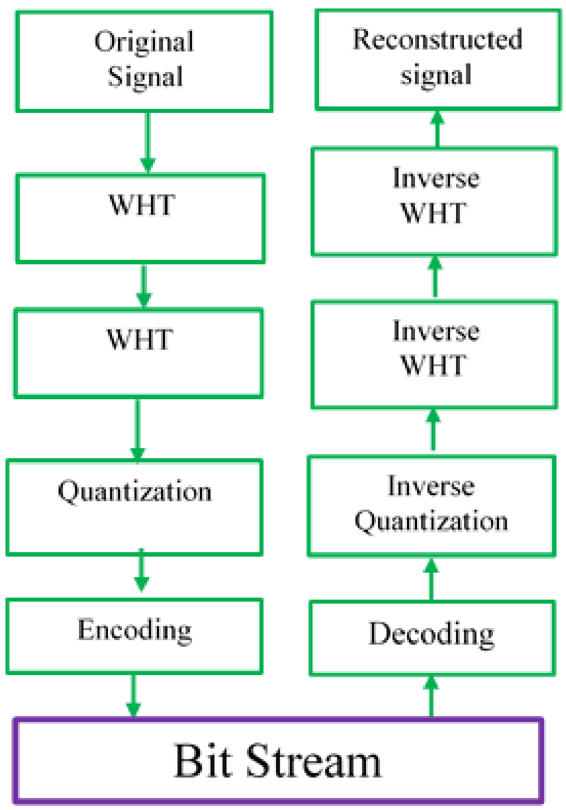

Fig 2. Proposed compression/decompression algorithm

Figure 2 shows the compression/decompression scheme that we propose. In this diagram, the vibratory signal is transformed by the Discrete Walsh-Hadamard Transform (DWHT). This transformation reduces redundancy in the temporal space. The coefficients obtained are transformed by the DWHT to reduce the residual redundancy in the frequency space. These coefficients are quantified to limit the number of bits to transmit. The quantified coefficients are coded by the Huffman coder. This results in a binary train. The signal reconstruction is done by going through the same steps in the opposite direction.

2.3.1 Walsh-Hadamard Transform

Walsh-Hadamard transform decomposes a signal s(t) into a set of orthogonal and rectangular functions called Walsh functions. Functions family of Walsh Wn(t) allows to approach any finite energy signal over an interval [0; T [.This makes it possible to achieve any desired precision by adapting the number N of the elements of the development. These functions take only +1 or -1 values by changing n times sign in the open interval [0; T [.The use of a vector with all values equal to (+1) or (-1) significantly reduces the computational complexity of the algorithm. The WHT has a fast decomposition algorithm with a computational cost O(NlogN) [24,25]. The analytical determination of these functions obeys the relation (2.6).

$$W_n(t) = \prod_{j=0}^{r-1} Signe\left\{\cos\left(n_j 2^j \pi \frac{t}{T}\right)\right\} \tag{2.6}$$

r is the smallest power of 2 greater than n.

n_j is the state of the j^{me} bit of the binary code of n.

$$n = \sum_{j=0}^{r-1} n_j 2^j \tag{2.7}$$

WHT performs a linear and involutive operation. In addition, it is orthogonal which allows its use in compression algorithms. We define Hm for m > 0 thanks to the relation (2.8).

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix} \tag{2.8}$$

The decomposition/recomposition by WHT for a signal s(t) of length N are defined respectively by equations (2.9) and (2.10).

$$a_n = \frac{1}{N} \sum_{i=0}^{N-1} s_i WAL(n,i),\ n = 1,\ 2,\ \ldots,\ N-1 \tag{2.9}$$

$$s_i = \sum_{n=0}^{N-1} a_n WAL(n,i),\ i = 1,\ 2,\ \ldots,\ N-1 \tag{2.10}$$

3 Results and Discussion

To ensure the compressibility of these data, we first represented the histogram of the vibration amplitudes values. This histogram is used to judge the level of redundancy of acquired data. It is shown in the Figure 3 .

Figure 3 shows the histogram of the vibration amplitudes of the ball bearing. This histogram shows that the signal distribution follows an almost normal law. It is noted that the largest quantity of data is that whose amplitude is between -0.5 micrometer and +1 micrometer, which is on average 60% of the data. This shows that the data are highly correlated, so one can presume the possibility of an effective compression of this signal. After compressing/decompressing these signals using the TDWH in two passes we obtained the results which are compared with those of Oyobe et al. [26] and recorded in Table 1 .

Table 1. Comparison of algorithms

	MSE	SNR	PRD	MFD	RC
Oyobe et al. [21]	2.11E-05	39.26	0.01	0.005%	78.21%
Proposed method	56E-04	15	55	0.005	96.3%

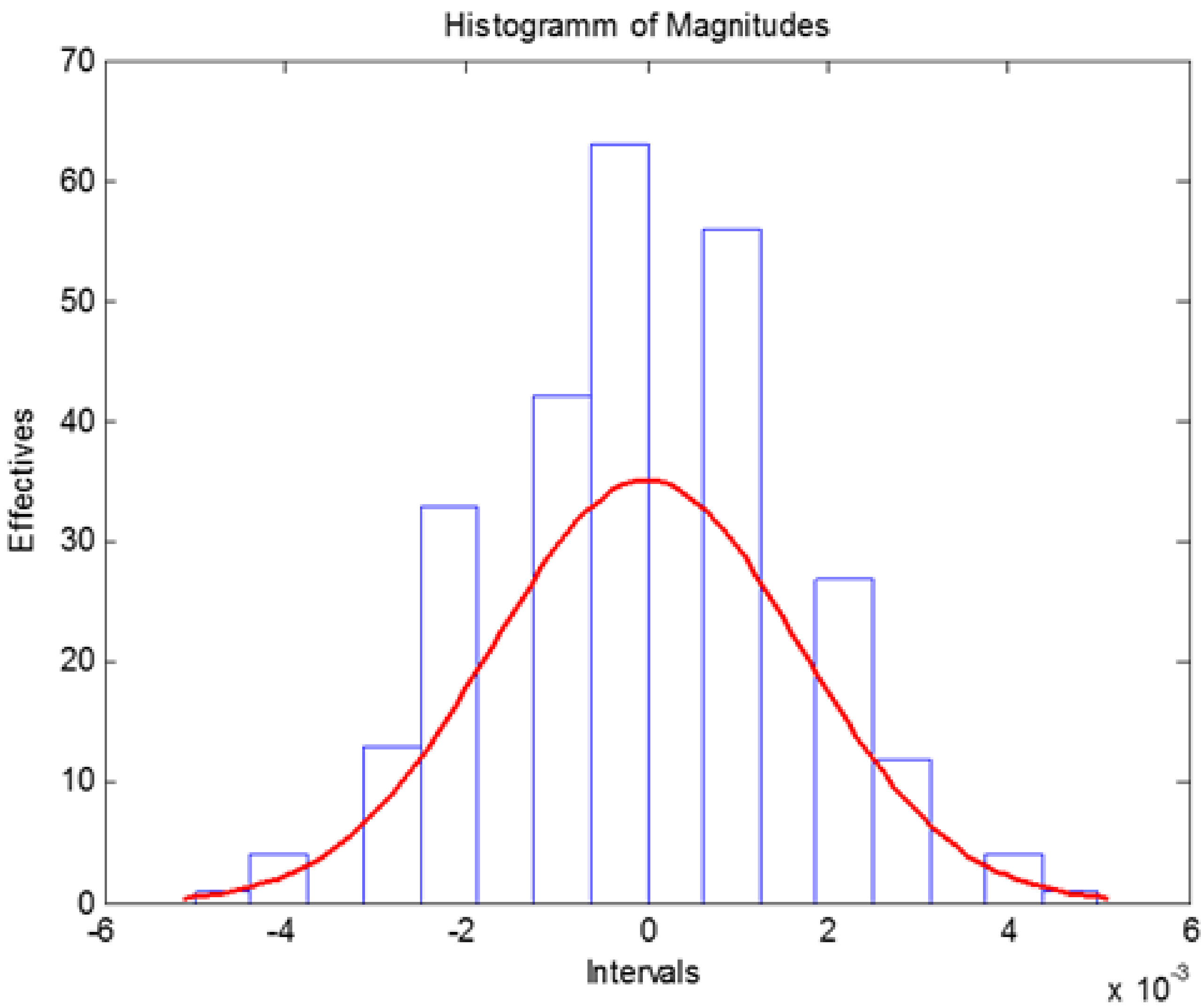

Fig 3. Vibration amplitudes distribution histogram

The compression/decompression results by this method are appreciated by the compression parameters whose values are: SNR=15 dB, MSE=56E-04, MFD=0.005% and RC=96.3%. The reconstruction error of the proposed method is a constant value and equals zero (because its value is nanometrical and therefore negligible); this confirms from an objective point of view, the good quality of the reconstructed data. The method offers a high compression ratio.

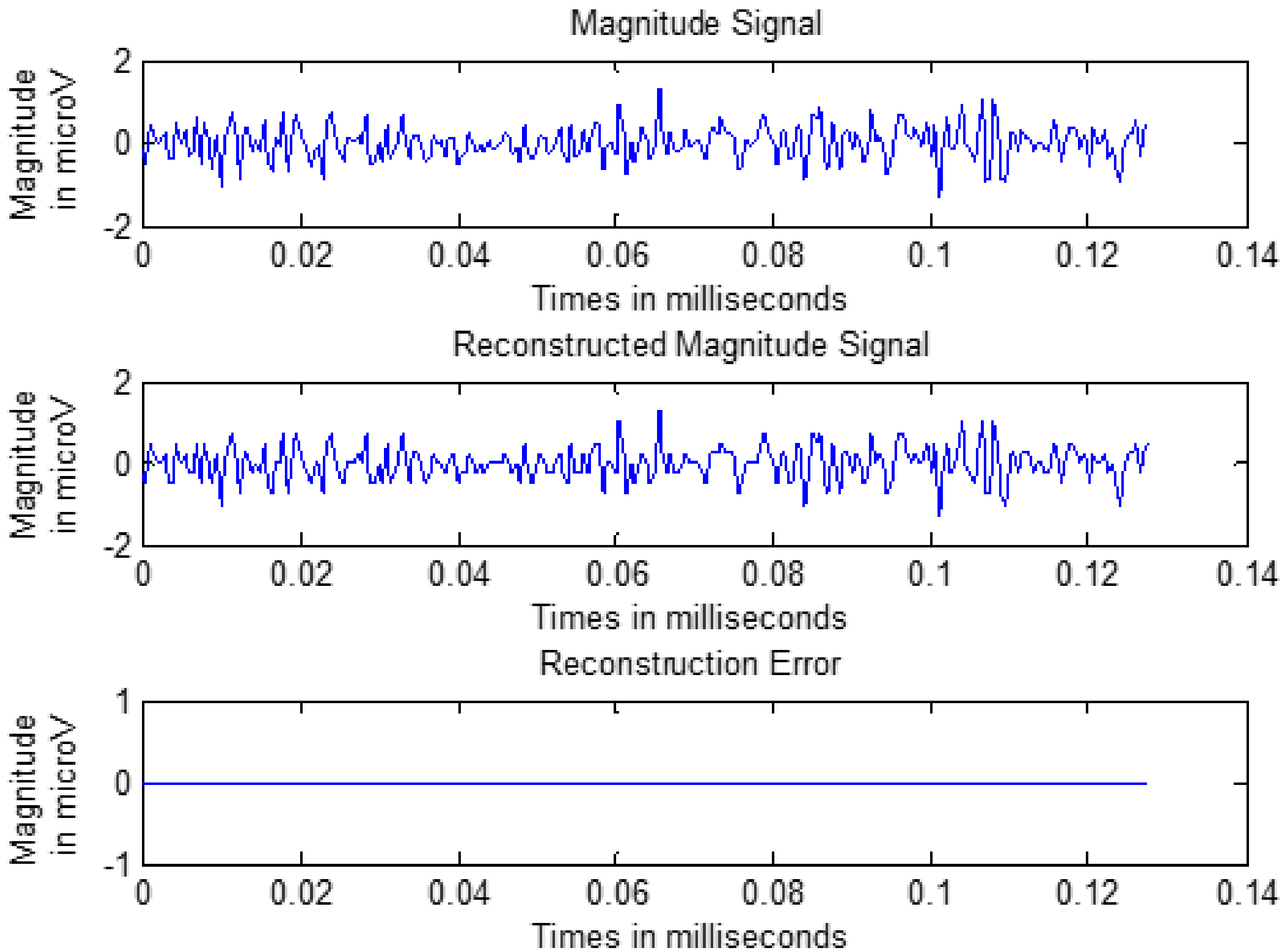

Fig 4. Signal representation: original, reconstructed and error

4 Conclusion

In this article, we presented a method for compressing/decompressing vibratory data. Table 1 shows that both qualitatively and quantitatively the proposed method gives very good results. Usually, compression methods by transformation have a nonzero reconstructed error. However, this bleaching of vibratory signals both in the temporal and frequency domain, followed by good quantization precision, allowed to cancel this error. Thus, the results obtained by this algorithm are encouraging in terms of objective and subjective criteria (SNR, MSE, MFD, CR and visual observation). Compression ratios are high when we consider that the reconstruction is almost perfect. However, after a state of the art on data compression, we found the non-existence of compression work on vibratory signals. One might think that there would be a transformation that would optimize the compression rate of these data for a more efficient compression for them.

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