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Compression of Vibration Data by the Walsh-Hadamard Transform

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Abstract: Vibration signals are vectors for several pieces of information relating to the operating status of rotating machines. The storage and transmission of these signals poses problems of space and bandwidth. One solution to this problem is to compress these signals. In this research, we compress and decompress the vibration signals formed by the variations of vibration amplitudesof a ball bearing. We used an algorithm based on the Walsh-Hadamard Transform (WHT). The coefficients obtained are coded according to Huffman coding. An evaluation of the performance of this algorithm is made on the basis of SNR, MFD, MSE, PRD and CR measurements. Taking this assessment into account, the results of the method are qualitatively and quantitatively very encouraging.

INTRODUCTION

Maintenance is an important activity in companies. This activity tends to evolve to meet the needs of responsiveness and cost. A particular development concerns the way of understanding the phenomena of failure. Failure prediction is essential for predictive maintenance because of its ability to prevent failures and maintenance costs. Vibration analysis is one of the tools for predicting failures in moving systems by the production of data that relate the state of the system. The acquired data are then the media for several pieces of information. This information takes up a lot of space and its transmission takes a lot of time. The aim of our research is to propose an algorithm for the compression of vibration signals resulting from the operation of a ball bearing. The parameters of interest during acquisition are vibration amplitude, speed and motion acceleration. In this research, we are interested in the variation of the amplitude of the vibration.

Several studies were carried out to monitor the evolution of vibration amplitudes while others aimed at extracting information contained in vibration[1]. In the literature, however, there is a scarcity of work on the compression of vibration data. Several signals were compressed. Yassine compressed the images using a coder based on progressive coding of data[2]. The coder used is EZW (Embedded Zero tree Wavelet). The compressed images were biomedical images. Kekre *et al*.[3] compressed the color images using an algorithm based on the Discrete Wavelet Transform (DWT). These images were color photographs. Barabi *et al*.[4] recorded and compressed images resulting from an endoscopy examination to facilitate their wireless transmission. Ishiguro Takehiko and Jay KIinuma compressed video signals to improve the transmission of color television images[5]. Amine NAIT-ALI studied biomedical data to improve the possibilities of their compression[6]. Saada and Zahra implemented an algorithm for compressing genome data[7]. The aim of this algorithm was to reduce the size of DNA information.

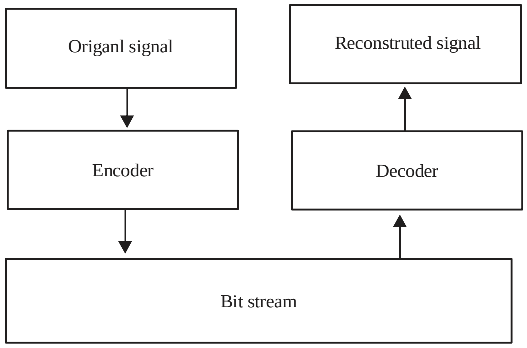

Fig. 1: Compression/decompression chain

Singh *et al*.[8] proposed an ECG data compression algorithm using the SPIHT (Set partitioning in hierarchical trees) encoder[11]. Prılepok compressed the EEG signal. The EEG signal is a complex signal; its compression makes it easier to understand. Indeed, this signal is the support of several brain activities. In 2019, Oyobe *et al*.[9] used the Walsh-Hadamard transform to compress the EMG signals. In the literature, vibration signal compression algorithms are rare if not almost non-existent, despite the well-known interest of compression in the storage and transmission of large data. To date, a compression algorithm involving the Walsh-Hadamard Discrete Transform (DWHT) as well as coding by the Huffman method, despite its potential has never been tested for vibration signal compression. The interest of this work is therefore justified by proposing an algorithm of compression of the vibratory data by the use of this method. This study consists of three parts: state of the art, methodology, analysis and interpretation of results.

State of the art

Generalities on the compression: The purpose of compression is to reduce the size of the data taking into account the quality of the reconstructed data. There are two types of compression: on the one hand, compression without loss of information, we are talking about reversible compression and on the other hand, compression with loss of information in this case, irreversible compression. In lossless compression, decoded information is the perfect image of the original information[10]. Its disadvantage is its low compression rate, especially when it comes to image compression. However, by means of lossy compression, high compression rates can be obtained but at the expense of the quality of the reconstructed signal[11]. The general diagram of compression follows the principle of Fig. 1.

Figure 1 shows the general data compression decompression procedure. The original signal goes through the encoder. In the case of lossless compression, the original signal is simply encoded and at the output a binary train is obtained. In the case of lossy compression in the encoder the original signal is decomposed by an orthogonal transformation. In this new space the transformed signal has a better representation and is sufficiently bleached. The coefficients obtained are quantified and coded. At the output of the encoder we get a binary train. The decompression follows this algorithm but in reverse.

In the literature, there is several data compression works based on orthogonal transforms. Several of them used DWT, DCT, KLT and WHT[12, 13]. Orthogonal transformation methods are known to be very effective in bleaching data. This remarkable efficiency is due essentially to two properties which are the parsimony of representation and the whitening of data[14]. The DCT, for example by bringing the signal into the frequency space, removes frequency redundancy. The transformation of Karhuen-Loeve on its side reorganizes the data in the same space but following new axes; this improves the compaction of these data. Thus, the Walsh-Hadamard transform will be used for this research.

Evaluation parameters: The compression ratio is an important parameter in the quantitative evaluation of a compression algorithm. It is defined in by:

$$RC = \left(1 - \left(\frac{\text{size of compressed file}}{\text{size of original file}}\right)\right) \quad (1)$$

It is the main criterion for evaluating a compression algorithm. However, when evaluating a lossy compression method, the qualitative parameters must be associated with this quantitative parameter. The qualitative compression parameters allow to give an opinion on the quality of the reconstructed signals. The most commonly used quality measure is Mean Square Error (MSE) and is defined by:

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

$S_0(n)$ = The original signal
$S_r(n)$ = The reconstructed signal
N = The number of samples of the signal

The most recommended measurement is the Signal-to-Noise Ratio (SNR):

$$SNR = 10\log\left(\frac{\sigma_x^2}{\sigma_e^2}\right) \quad (3)$$

With σ_x^2 represents the power of the original signal and represents the power of the error. In[15] and two other criteria for assessing the reconstructed signal quality are presented: the distortion of the mean frequency MFD (Mean Frequency Distortion) and the PRD (Percent Root mean square Difference)[15]. They are defined by:

$$MFD = \left(\frac{|F_{orig} - F_{recons}|}{\max(F_{orig}, F_{recons})} \right)^2 \quad (4)$$

In Eq. 4, Forig and Frecons represent the average frequency calculated respectively on the original signal and on the reconstructed signal:

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1}(s(n) - \hat{S}(n))^2}{\sum_{n=0}^{N-1}(s(n) - \hat{S}(n))^2}} \times 100\% \quad (5)$$

Where:

s(n) = The original signal
s(n) = The reconstructed signal
N = The number of points of the original signal
μ = The CAN reference value used for data acquisition

MATERIALS AND METHODS

Compression/decomposition procedure: The compression/decompression scheme implemented in our algorithm is given in Fig. 2. Figure 2 shows the compression/decompression scheme we propose. In this scheme the vibratory signal is transformed by the Discrete Walsh-Hadamard Transform (DWHT). This transformation reduces redundancy in the frequency plane. The coefficients obtained are quantified to limit the number of bits to be transmitted. The results of this quantification are coded according to the Huffman algorithm. We get a binary train. Signal reconstruction is done by following the same steps in the opposite direction.

Walsh-hadamard transform: The Walsh-Hadamard transform is a non-optimal and orthogonal transformation. It decompse a s(t) signal into a set of orthogonal and rectangular functions called Walsh functions. The Walsh Wn(t) family of functions allows to approach any finite energy signal over an interval [0; T [.These functions form a complete set. This allows 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 of sign in the open interval [0; T [.Using 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 calculatory cost O(Nlogn)[16, 17]. The analytical determination of these functions is governed by Eq. 6:

$$W_n(t) = \prod_{j=0}^{r-1} \text{Signe}\left\{ \cos\left(n_j 2^j \pi \frac{t}{T} \right) \right\} \quad (6)$$

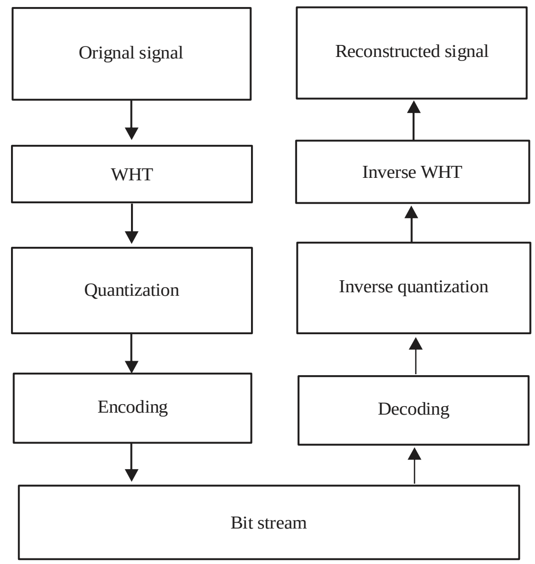

Fig. 2: Proposed compression algorithm

Where:

r = The smallest power of 2 greater than n
n_j = The status of the j[th] bit of binary code of n

$$n = \sum_{j=0}^{r-1} n_j 2^j \quad (7)$$

The Walsh-Hadamard Transformation is the simplest of the transformations to be implemented easily. It performs a linear and involutive operation. In addition, it is orthogonal which allows its use in compression algorithms. Recursively, we define a first transformation 1x1 through a H_0 matrix which is the identity matrix with a single element 1. We then define H_m for thanks to the relationship (3):

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix} \quad (8)$$

The decomposition/reconstruction by the WHT transform for a s(t) signal of length N is defined by Eq. 4 and 5, respectively:

$$a_n = \frac{1}{N} \sum_{i=0}^{N-1} s_i WAL(n,i), n = 1,2,\ldots,N-1 \quad (9)$$

$$s_i = \sum_{n=0}^{N-1} a_n WAL(n,i), i = 1,2,\ldots,N-1 \quad (10)$$

The resulting WHT coefficients are coded according to Huffman's coder.

RESULTS AND DISCUSSION

The method presented in this study has been implemented on a real vibratory signal. These are records of the vibration monitoring of a ball bearing. The reference for this ball 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 12-bit CAN for scanning acquired data. The vibration parameter chosen for this work is the amplitude variation.

Since, the vibration signal is very little known in the literature of data compression, we first represented the histogram of vibration amplitude values. This histogram allows a visual assessment of the level of data redundancy. It is shown in Fig. 3 and 4.

Figure 3 is obtained by constructing the histogram of the vibration amplitude signal of the ball bearing. This histogram shows that the distribution of the signal follows an almost normal law. The redundancy of the data can be observed with regard to the shape of the histogram. Note that the largest amount of data is the one with an amplitude between -0.5 micrometer and +0.5 micrometer. The data are highly correlated, this implies the possibility of efficient compression of this signal. Correlated signals lend themselves well to compression. In this research, we compressed/decompressed the vibration signals (amplitude variation) using the Discrete Walsh-Hadamard Transform (DWHT). The results of this compression/ decompression are recorded in Table 1.

The results presented in Table 1 show the qualitative and quantitative differences between the different reconstructed signals for different quantization accuracies.The two quantization steps give the same value of the Mean Frequency Distortion (MFD) of 0.005%. This very small MFD value indicates that the method is stable in frequency. The compression ratio improves at the expense of the reconstructed signal quality. According to the results presented in Table 1 for an accuracy of one hundredth the compression ratio is better (96.87%). However, taking into account the fact that the processing of this signal helps to the maintenance of industrial systems (therefore very sensitive) and the increase in the mean square error (reduction of the reconstructed signal quality), we can chose the algorithm at the lower compression rate and at the best reconstructed signal (78.21%). The role of the DWHT in this algorithm is to perform the whitening of this data. This whitening is a

Table 1: Evaluation of the DWHT algorithm

Quantization step	MSE	SNR	PRD	MFD (%)	RC (%)
E-2	23E-04	18.98	11.22	0.005	96.87
E-3	2,11E-05	39.26	0.01	0.005	78.21

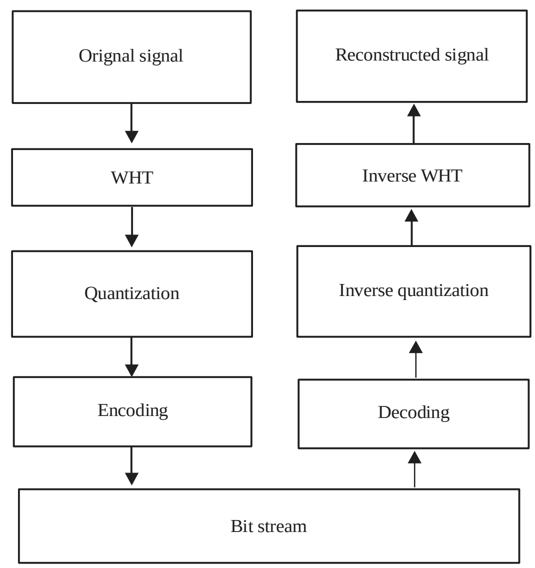

Fig. 3: Vibration amplitude distribution histogram

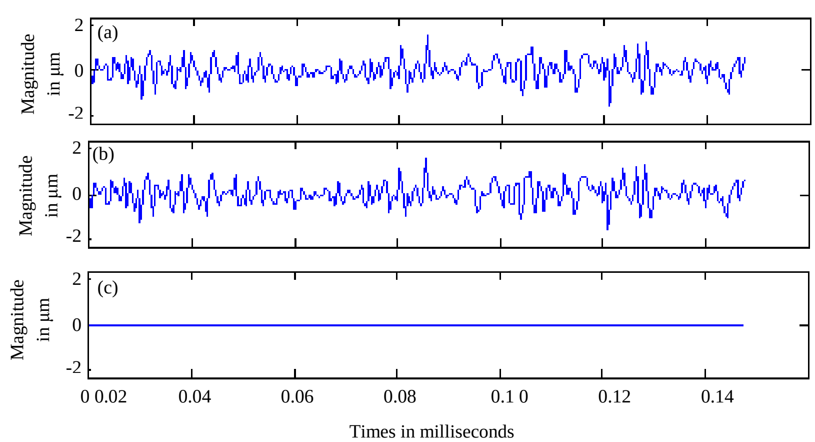

Fig. 4(a-c): Comparative representation of signals: original, reconstructed and error first step of compression by removing data redundancy in the frequency plane. After quantization of coefficients, Huffman coding is used as a second step of compression that optimizes the first step. The results of compression/decompression of the proposed algorithm are shown in Fig. 4.

The result of compression/decompression by this method is evaluated by the compression parameters, the values of which are: SNR = 39.26dB, MSE = 2.11E-05, MFD = 0.005% and RC = 78.21%. The reconstruction error of the proposed method is a constant value and equals zero; this confirms from an objective point of view the good quality of the reconstructed data. Its compression ratio is high.

CONCLUSION

In this study, we presented a method for compressing/decompressing vibration data. It is apparent from Table 1 that the proposed method, qualitatively and quantitatively gives the good results. Typically, the compression by transformation methods has a non-zero reconstruction error. With vibratory signals, good quantization accuracy cancels this error. Thus, the results obtained by this algorithm are encouraging with regard to objective and subjective criteria (SNR, MSE, MFD, CR and visual observation). This method has a moderate computational load because it uses a linear transformation. The compression rates are high considering that the reconstruction is almost perfect. However, after a state-of-the-art on data compression, we found that no compression work existed on vibration signals. This absence offers an additional line of research on vibration signal compression. This allows us to optimize the storage space for further study.

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