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A New Compressing Ultrasonic Data Algorithm Based on Wavelets

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Abstract: In this paper, we propose a novel and effective algorithm for compressing large volumes of data recorded in underwater applications, using a laboratory designed experimental setup. This data represents samples of ultrasonic signals acquired at different geometric positions of a water tank. The proposed algorithm was based on Wavelets and consists of two processing phases including a prefiltering stage using wavelets to eliminate non significant values thus reducing the number of nonzero coefficients and a second processing stage to eliminate the redundancies present in the signal.

Key words: Wavelet, compression, de-noising, sonar, data acquisition

INTRODUCTION

Underwater objects identification is of a great importance to a large number of environmental problems and civilian applications[1-6], such as seabed mapping, archaeological object recognition, and wreckage detection. The availability and the expensive cost of ultrasonic tests in real mediums such as sea and lakes has led to the use of laboratory tanks for measurements, with gated signals and time-windowing to isolate reflections. Laboratory tanks have the advantage of providing more controlled experimental conditions, but their use introduces further measurement problems, since the signal detected by the ultrasonic transducer is contaminated by transients due to the resonance of the devices, and the noise potentially from both acoustic and electrical sources. On the other hand, in conducting underwater experiments, and especially in the seabed mapping and underwater object identification applications, a large quantity of data saving on disk is required. Hence, it is necessary to develop a data compressing algorithm.

Many research studies have been conducted on underwater object detection using a variety of laboratory experimental setups and signal processing techniques. Among the most important problems encountered in this type of application is the large amount of information to be acquired and saved for further processing and analysis. Hence, it is necessary to develop an algorithm to compress data to optimize the storage size on discs. Compressing is used to remove redundancies while retaining as much as possible the important signal features. In the recent years a considerable interest has arisen regarding the use of Wavelet as a new transform technique for signal processing applications. This technique has shown effective results in several applications such as nonlinear noise filtering, image and signal compression, edge detection and feature extraction[5-13].

In this study, we first propose an experimental setup developed to conduct laboratory underwater experiments. The proposed system can be used to model a number of sonar applications such as underwater object identification, seabed mapping and many others. Then, we propose a novel effective algorithm based on Wavelets to compress the large volumes of data recorded, for further use. The compression algorithm eliminates redundancies in the signals. The experimental results show that the proposed algorithms are very effective and achieve high rates of data compression.

MATERIALS AND METHODS

Data acquisition: The conceived data acquisition system of Fig. 1 represents a laboratory-scale experimental setup consisting of primarily a water tank, an ultrasonic transducer, three interface cards and a personal computer for the control of the global system. The transducer device has a central frequency of 2.25 MHz and is carried by a three-axis translational mobile system moving over water surface in the tank. The position of the transducer along the x, y, and z axes is controlled by three stepper motors[5]. The experiment consists of placing an object target at the bottom floor of the tank and scanning its surface by means of ultrasonic signals generated by energizing the transducer using a discrete-frequency true sinusoidal tone-burst signal of finite duration. The ultrasonic transducer translates the electrical signal into mechanical vibrations transmitted within the elastic medium and then reflected and refracted at the impact of the object target or the bottom floor. The orientation of the flux of reflected and refracted waves are defined by the well known Descartes laws of optics where the optic index is replaced by the speed C of the acoustic waves[5, 6].

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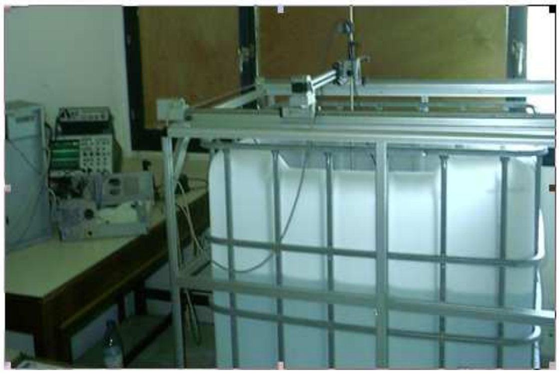

Fig. 1: The experimental setup

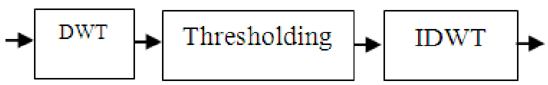

Fig. 2: First phase compressing bloc

The reflected waves will be detected by the transducer translating them into electrical signals named echoes, which will later be amplified and filtered. These returned ultrasonic echoes are then sampled and acquired at uniformly spaced times by use of a 12 bits analogue-to-digital converter, with a sampling rate of 10M samples per second. For each position of the transducer, the converted samples are directly buffered in an on board FIFO memory of 32K. The transfer of these samples from the FIFO memory to the hard disk of the computer is done through the PCI bus attached to a DMA which can perform the transfer without the intervention of the main processor. The saving of the acquired data is kept in files having names composed by two fields. The first field is a constant chain of characters that represents the basic name set by the user and the second field is an index automatically incremented as the transducer will be shifted from a position to another. For each position scheduled for taking a measurement, it is necessary to acquire 10,000 samples. This allows the collection of all the returning echoes of the target as well as the water tank bottom floor. Knowing that the spatial (geometric) sampling depends on the wavelength of the used ultrasonic transducer as well as the distance that separates the transducer from the bottom floor of the water tank, the displacement step has to be set to a value less or equal to three millimeters. This small displacement value along the x-y axis implies a large number of sample files. Since the size of every file is about 98 Kbytes, a large quantity of saving on disk of almost 500 Mbytes is required. Hence, it is necessary to develop a data compressing algorithm. We propose a technique based on Wavelets transform.

The received signal contains much information, which is the result of all the acoustic properties of the encountered media: acoustic impedance, attenuation and speed of the ultrasounds waves, and material density[6]. In the received signal from the transducer, we can focus on different things depending on the application. We can for example focus on the echo arriving instants to localize a target, the time intervals that separate these echoes for a measurement of thickness, or the altitude and the amplitude as a function of time of the filtered and rectified signal for the recognition of the type of material.

We developed an effective compressing algorithm to remove redundancies while retaining as much as possible the important signal features.

Data compression: The wavelet transform is a key ingredient in most state-of-the-art signal and image compression algorithms, including the recent JPEG-2000 standard. A concrete connection between lossy compression and denoising can be seen when one examines the similarity between thresholding and quantization[12]. Others works[7,13], also addressed the connection between compression and denoising, especially with nonlinear algorithms such as wavelet thresholding in a mathematical framework. However, these works were not concerned with quantization and bitrates: compression results from a reduced number of nonzero wavelet coefficients and not from an explicit design of a coder.

The proposed compressing algorithm consists of two phases: the first phase is based on Wavelets and aims to reduce the numbers of none zero coefficients by eliminating the non significant values. The second processing stage is used to eliminate the redundancies present in the signal.

RESULTS AND DISCUSSION

Phase 1 of the compressing algorithm: The first phase compressing algorithm is based on Wavelets and aims to reduce the numbers of nonzero coefficients by eliminating the non significant values, more likely due to noise. The algorithm consists of using the wavelet transform with thresholding techniques to denoise the different signals, thus replacing non-significant values by zeros.

The Discrete Wavelet Transform (DWT) analysis, is based on the assumption that the amplitude rather than the location of the spectra of the signal to be as different as possible from the amplitude of noise. This allows clipping, thresholding, and shrinking of the amplitude of the coefficients to separate signals or remove noise. It is the localizing or concentrating properties of the Wavelet transform that makes it particularly effective when used with this nonlinear filtering method[8].

Thresholding generally gives a low pass and smoother version of the original noisy signal. Wavelet thresholding technique which was first proposed by Donoho is a signal estimation method that exploits the capabilities of Wavelet transform for signal denoising and has recently received extensive research attentions[9]. In this approach, the processing is carried on in the transform domain. The DWT of the signal is calculated and the resultant wavelet coefficients are compared to some thresholds. Since the wavelet transform is good at energy compaction, the small coefficients are more likely due to noise that has its energy spread over a large number of coefficients and large coefficients due to important signal features. These small coefficients can be thresholded without affecting the significant features of the signal.

Thresholding is a simple non-linear technique, which operates on one wavelet coefficient at a time. Two types of thresholding are used: hard thresholding and soft thresholding. For a threshold δ, the hard thresholding technique is obtained by:

$$THR_H(d_j(k),\delta) = \begin{cases} 0 & \text{if } |d_j(k)| \le \delta \\ d_j(k) & \text{if } |d_j(k)| > \delta \end{cases} \quad (1)$$

In the soft thresholding case, for the same threshold the calculation is given by:

$$THR_S(d_j(k),\delta) = \begin{cases} 0 & \text{if } |d_j(k)| \le \delta \\ \operatorname{sgn}(d_j(k))|d_j(k)-\delta| & \text{if } |d_j(k)| > \delta \end{cases} \quad (2)$$

The soft thresholding results in a smooth reduction of all coefficients toward zero and sets equal to zero those closest to the origin. Applied to our ultrasonic signal, the soft thresholding has provoked an important attenuation of its level. This has necessitated compensation before applying the inverse wavelet transform that gives a de-noised ultrasonic signal. The application of hard type thresholding preserves discontinuities present in the ultrasonic signal without level compensation hence justifying its use.

As for the choice of the threshold several methods are used according to applications. However, few methods are specifically designed for use with ultrasonic signals. In[4], a relative threshold level representing a fraction of the absolute value of the largest coefficient is used to filter an acoustic data collected from an acquisition system based on parametric sonar. Other types of thresholds such as absolute quantitative threshold, relative quantitative threshold, absolute threshold, the thresholds VisuShrink[8] and SureShrink[10] of Donoho and Johnston as well as many other complex thresholding methods are proposed in literature.

In this study, we have tested the VisuShrink threshold of Donoho and Jonhson which consists of the following level value to process a set game of N coefficients:

$$\lambda = \sigma\sqrt{2\log(N)} \quad (3)$$

σ represents the noise variance. This threshold did not produce satisfactory results for the ultrasonic manipulated signals. In fact, the noise assumption used in Donoho's derivation fails when a signal is not contaminated by additive Gaussian noise or as the size of the signal gets smaller[11]. The threshold values for the different coefficients of the Wavelet are chosen after a detailed analysis of an example acquired ultrasonic signal. The analysis is performed at a geometric position for which we know the returning echo position. According to this study, we have performed a suitable threshold for every useful coefficient before proceeding to the reconstruction and the saving of the de-noised ultrasonic signal. The chosen absolute levels gave better results with a faster execution time, without loss of useful information.

The proposed algorithm consists of a wavelet decomposition of ultrasonic signals. This decomposition was performed by using the Sym6 mother wavelet up to level 4. The choice of Sym6 is based on the similarities that have been noticed between this mother wavelet and the returning ultrasonic echoes to be identified. Figure 4 illustrates the de-noising results for the example acquired ultrasonic signal shown in Fig. 3.

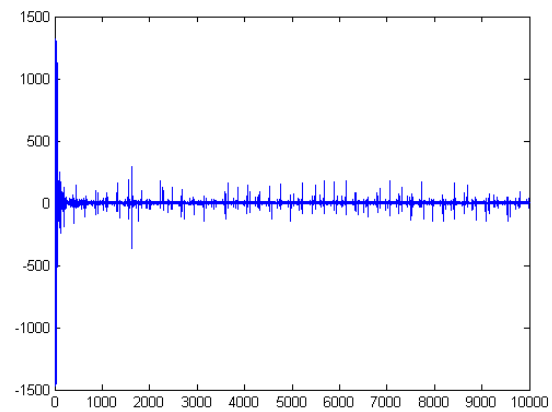

Fig. 3: An example of ultrasonic acquired noisy signal

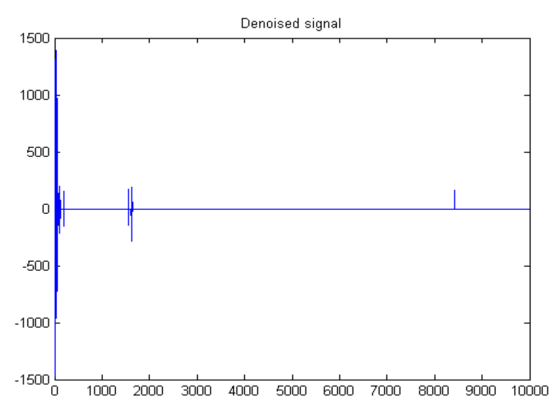

Fig. 4: De-noised signal using the 1 phase of the compressing algorithm

We can see that the number of none zero values represented in Fig. 4 is considerably reduced without losing the useful information consisting of the position of the returned echo reflected at the impact of the upper surface of the underwater object target.

Phase 2 of the compressing algorithm: The nature of the acquired ultrasonic signals is to present echoes of important amplitudes and relatively short duration with respect to the intervals where the signal is normally absent (zero amplitude). We have developed a new algorithm capable of compressing large volumes of data by eliminating redundancies present in the signal. The coding scheme in this case is very simple. It consists of taking an ensemble of data as inputs then counts the number of zeros between two consecutives nonzero values. The method provides the code of that represents the sequence of zeros. This method is very useful and efficient when applied to a source including large and numerous sequences of zeros as in our case.

For each point scheduled for taking a measurement, it is necessary to acquire 10,000 samples. This allows the collection of all the returning echoes of the target as well as the water tank bottom floor. The size of the file that contains the raw unprocessed data is equal to 98 Kbytes. After compression, using the developed algorithm, the size of every file is reduced to a value between 460 bytes and 800 bytes depending on the number and the importance of echoes that the file presents. Hence, we achieve a compression rate of 99.4%.

CONCLUSION

In this study, we have proposed an effective algorithm for compressing large volumes of ultrasonic data recorded in underwater applications, using a laboratory designed experimental setup. The proposed algorithm is based on Wavelets. A concrete connection between lossy compression and denoising was noticed since there is a similarity between thresholding and quantization. High rates of data compression were achieved. This study showed how effective wavelet based approaches can be in signal denoising and data compression.

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