Simulation Study of an Ultrasonic Signal Compression

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Abstract The paper presents three algorithms of an ultrasonic signal compressing. First one is a compression with linear time quantization. Second algorithm of signal compression calculates the rate of signal change and proportionally to it sets the sampling rate. Third algorithm of compression takes some number of random uniformly distributed samples from the original ultrasonic signal. The results of simulations for all three compressing algorithms are presented in the paper. An absolute error and mean square deviations for a wide range of compression ratios are calculated and compared for different compressing algorithms.

1 Introduction

Ultrasonic phased arrays are widely used in different fields of non-destructive testing. Higher accuracy of defect detection demands grater resolution of the ultrasonic installation, which necessitates the increase in the array element number. The increase in

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the element number, however, leads to larger amounts of data obtained and transmitted from sensors to processor unit. Large data arrays require higher transmission capacity of communication channels, as well as higher capacity of memory devices.

The solution to the problem of reducing the amount of data without distorting the results of testing is the use of a signal compression algorithm. Nowadays, different algorithms of data compression are developed [1–8]. Wavelet transforms are widely used to compress and filter signals [1–3]. A review of the use of wavelets for processing the ultrasonic signals showed that the wavelet transform was used mainly to improve the detection of defects by increasing the signal-to-noise ratio.

In the last decade, a new approach to signal processing, called compressive sensing [4–7], has become popular. This approach proposes measuring only the significant parts of the signal instead of obtaining its values on all samples. Thus, if the significant part of the signal is small when compared to the entire signal, then you can significantly reduce the amount of data processed and transmitted. Moreover, the approach allows filtering out unnecessary information already at the measurement stage, i.e. before the stages of data transmission and processing. Filtering procedure is executed at the physical level, with no use of computing resources and, therefore, with no time delays associated with computations [6].

In the works [7, 9] compression algorithms are described, in which inflection points and extremes are used as significant parts of the signal. Such algorithms have been used for processing and transmitting ultrasound data in medicine.

The compressive sensing problem arises in design of modern telecommunication systems of transfer of telemetry information through borehole pipe as evanescent waveguide that is not on the basic signal mode [10]. The information transfer problem through such communication channel is initially stage of development. Sand and drilling agent lead to sharp increase of attenuation. For deepest boreholes up to 2.5–3 km the overcoming of strong attenuation is the urgent technical problem. Radiophysical investigations show that frequency should be above to receive the maximum power of radiation and at the same time less for attenuation decrease in the filling media. Therefore, ultrasonic signal is the only suitable for the considered communication channel. But the use of the ultrasonic signal for telemetry transfer leads to low rate transfer. It leads to necessity of investigation of algorithms and ways of ultrasonic signal compression with losses that transferring all necessary data in real time.

2 Compression Ratio and Quality of Signal Reconstruction

The effectiveness of the compressing algorithm is characterized, first of all, by the compression ratio ***k***, which determines the ratio of the number of bit symbols of the original N and compressed signal M:

$$k = \frac{M}{N} \tag{1}$$

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To estimate the quality of the reconstructed signal, the reduced error is calculated:

$$\gamma = \frac{x(n) - y(n)}{X} \times 100\% \tag{2}$$

where $n = 1 \ldots N$; N is the number of signal samples in the interval; $x(n)$ are samples of the original signal, $y(n)$ are samples of the recovered signal; X is the upper limit of the scale.

Also, to estimate the accuracy of signal reconstruction, the mean square deviation is used:

$$\delta = \sqrt{\frac{\sum_{n=1}^{y} [x(n) - y(n)]}{N}} \tag{3}$$

3 Signal Compression with Linear Time Quantization Algorithm

Fist algorithm to compress an acoustic signal is a linear time quantization compressing, i.e. sampling the signal with equivalent time intervals and fixed sampling frequency. When decreasing sampling frequency the number of samples also decreases and sampled signal is getting more and more compressed.

Let's now simulate this algorithm of regular compressing using MatLab Simulink. For this purpose we generate example signal of sinusoidal shape to demonstrate the proposed algorithm of compressing. Than we sample this signal with a help of pulse generator, the pulse frequency of which we can vary. Figure 1 shows the regular compressing algorithm: sin-wave signal, sampled sin-wave signal, reconstructed signal, absolute error of reconstruction.

This algorithm of regular compression was applied to compress an ultrasonic echo-signal, the model of which is presented in Fig. 2. Resulting signal is presented in Fig. 3.

The number of samples M was varied from 8000 to 400 which corresponded to a change of compression ratio in the range from 1 to 20. After modeling the graphs of absolute error and mean square deviation σ of the reconstructed signal versus compression ratio k were obtained (Fig. 4). Absolute error was calculated as a difference between compressed and original echo-signals signals.

The results of simulation show proportional increase in absolute error and mean square deviation with increasing compression ration $\boldsymbol{k}$ from. Therefore, the compressing algorithm based on linear time quantization of ultrasonic signal is inappropriate for signal compression with high ratios (more than 5) since the error exceeds 10% value.

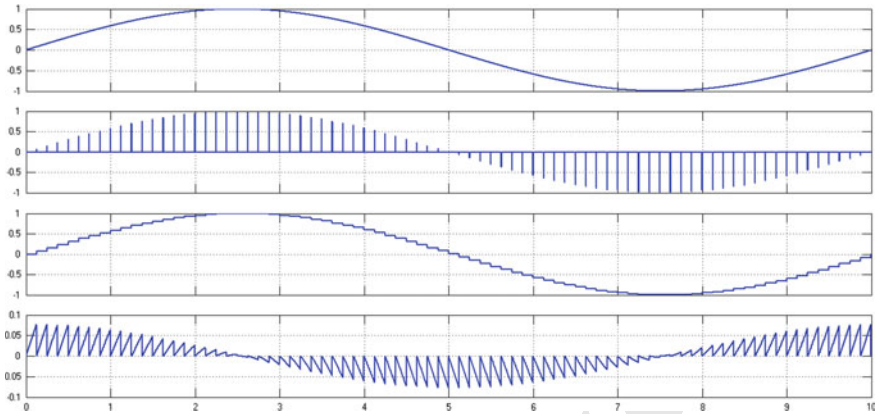

Fig. 1 Regular compressing of sin-wave input signal: input sin-wave signal, sampled sin-wave signal, reconstructed signal, absolute error of reconstruction

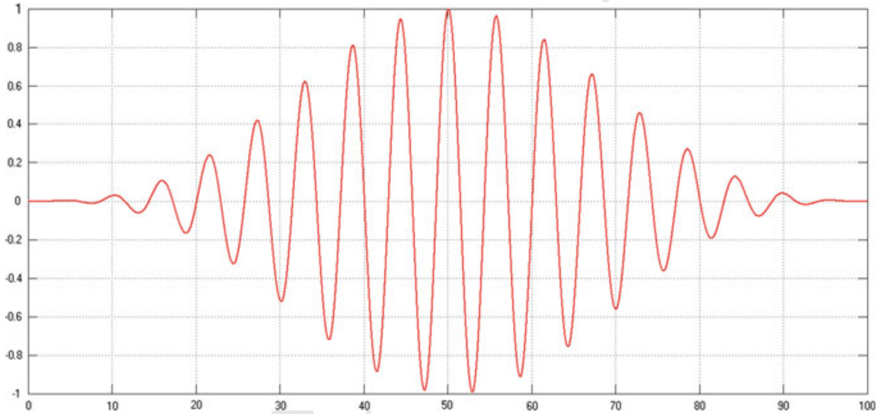

Fig. 2 The ultrasonic signal model

4 Signal Compression with Algorithm Based on Calculation of the Rate of Signal Change

The next algorithm is based on the calculation of the rate of change of input signal. In accordance with the rate of change of the signal, the sampling rate of the analog signal into a digital code is calculated. Therefore, the higher is the rate of change of a signal, the higher is the sampling rate, and vice versa. Thus, in the absence of a signal and at low rates of change of the signal (rate tends to zero), the sampling rate is very small and tends to zero; therefore, the conversion of such insignificant parts of the signal into a digital code will not performed.

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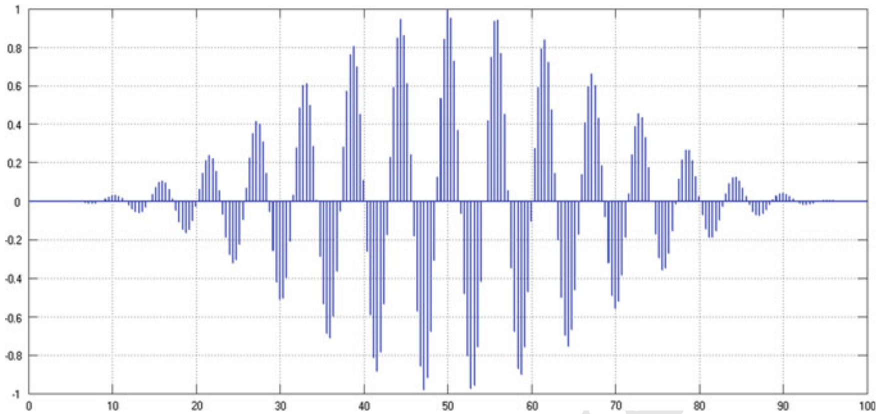

Fig. 3 The ultrasonic signal compressed with linear time quantization algorithm

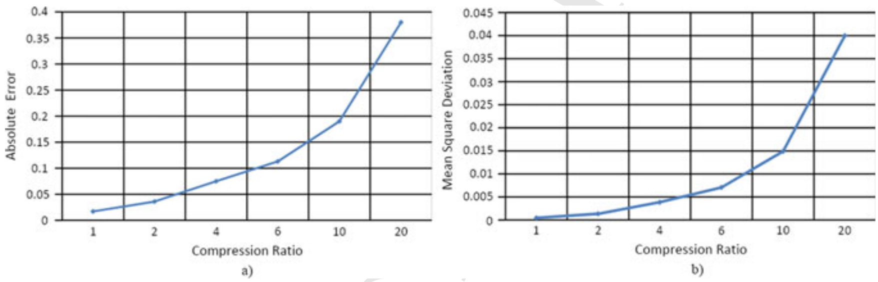

Fig. 4 Absolute error (**a**) and mean square deviation (**b**) versus compression ratio of signal (Fig. 3)

To sample input analog signal the voltage-to-frequency converter (VFC) was implemented in the model, which provides an output frequency accurately proportional to its input voltage.

Figure 5 demonstrates the performance of the algorithm of the progressive compressing.

Progressive compressing was applied to an ultrasonic echo-signal (Fig. 2). Resulting signal is presented in Fig. 6. The number of samples M was varied from 7000 to 350, which corresponded to a change of the compression ratio k in the range from 1 to 20. The graphs absolute error and mean square deviation of the reconstructed signal versus compression ratio were obtained (Fig. 7).

The modeling shows slower increase in absolute error as well as in mean square deviation for varied compression ratio in comparison with results of compression modeling with linear time quantization algorithm (Fig. 4). Compression ratio $k = 20$ showed less than 10% value of absolute error and mean square deviation less than 0.02.

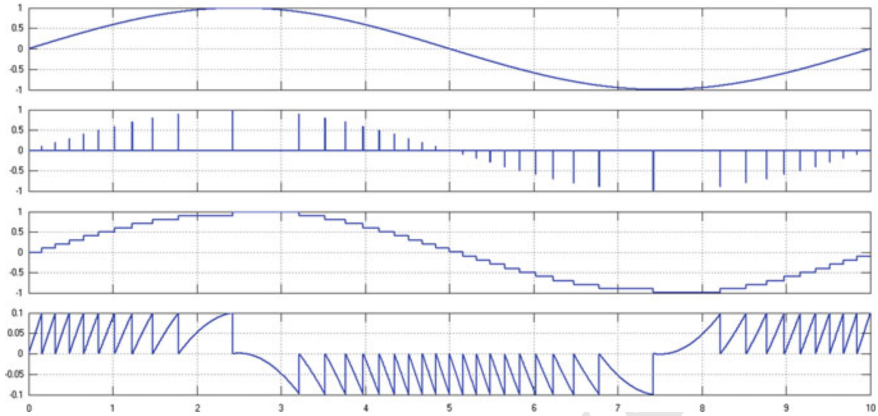

Fig. 5 Progressive compressing of sin-wave input signal: input sin-wave signal, sampled sin-wave signal, reconstructed signal, absolute error of reconstruction

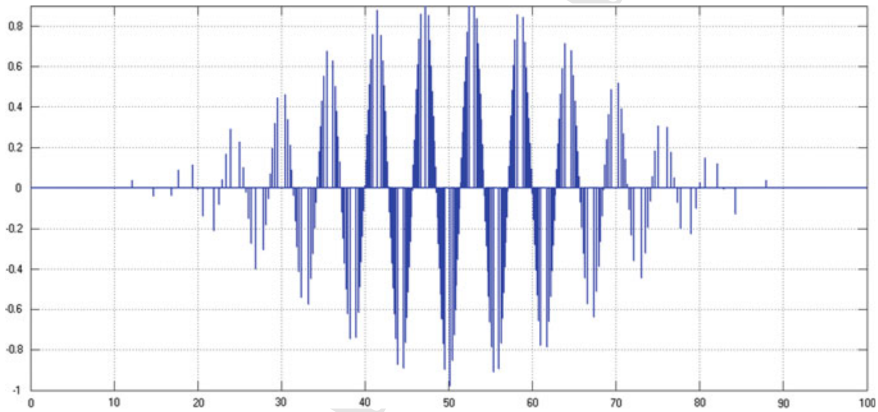

Fig. 6 The ultrasonic signal compressed with algorithm based on calculation of the rate of signal change

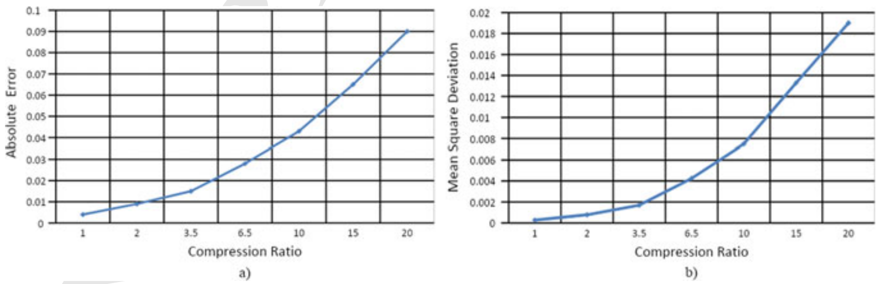

Fig. 7 Absolute error (**a**) and mean square deviation (**b**) versus compression ratio of signal (Fig. 6)

5 Signal Compression with Random Sampling Algorithm

In [9] authors offer algorithm of signal compression based on a choice in real time key points where extremes and points of the maximum curvature of function are presented. We will show that information losses in this case will be increased in more times rather than more samples are presented in signal.

For example, we will consider a model of the ultrasonic pulse well described by the formula:

$$y(t) = \sin \Omega t \sin^3 \omega t,$$
$$\Omega = 10, \omega = 0.3, t \in [0.001; 10] \tag{4}$$

Let 10,000 discrete values of this signal be total amount of the signal. We take random uniformly distributed M samples $y_i(t)$ from this signal (Fig. 8) calculated in Statistica 8.0 software [11].

Mean square deviation σ for 10 random samples is presented in Fig. 9. Compression ratio k is total amount of samples (10,000) divided on quantity of points in the sampled signal. As a result of nonlinear evaluation in the "Nonlinear Estimation" module of Statistica software it is found that mean square deviation of the restored signal from initial is inverse proportion to compression ratio:

$$\sigma(k) = 0.0038 + 0.00019/k - 0.0036/k^2 \tag{5}$$

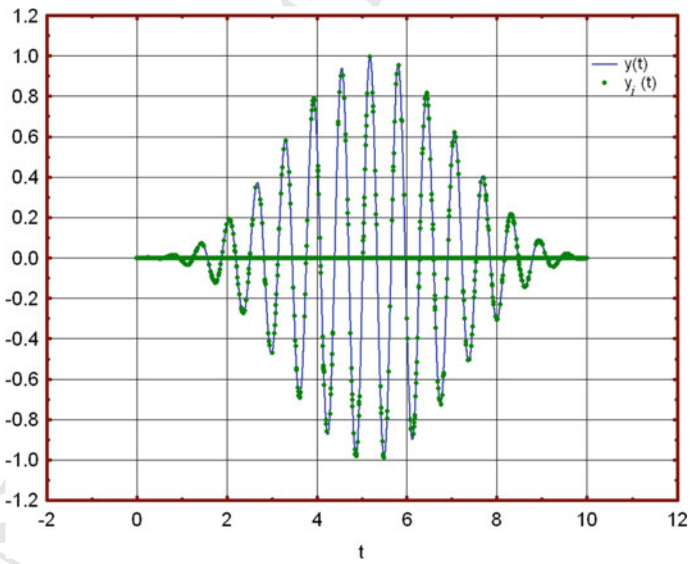

Fig. 8 The ultrasonic signal model

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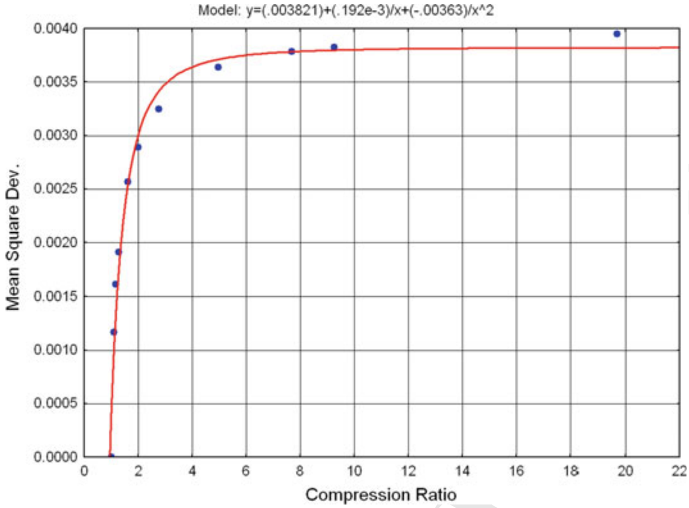

Fig. 9 The mean square deviation for random samples (Fig. 8)

At reduction of *M* quantity that is increasing of the compression ratio, the mean square deviation for samples will be sharply increased. Then in the domain of small volume of samples at compression of five times and more the mean square deviation changes a quite little, but information losses in this domain are already considerable. If we choose the key points that authors of [11] offer, the quantity of samples will be essential less than 2000 for our example that is compression ratio will be more than five times. It will catastrophically affect to the signal restoring accuracy. We will show it by restoration of the signal compressed twice. The initial values of frequencies Ω and $\boldsymbol{\omega}$ in the "Nonlinear Estimation" module was closed to true, $\Omega = 10.5$, $\omega = 0.35$. If compression ratio was less than two, the exact values Ω and $\boldsymbol{\omega}$ have been founded, but for compression more than twice *k* are essentially distinct from (4): $\Omega = 10.03$, $\omega = 0.397$ (Fig. 10).

Besides, the small deviation of the ultrasound signal amplitude from real is less critical for restoration losses, but some weakest deviation of frequency leads to essential distortions.

Form of curve described by (5) remains the same for any form of the ultrasonic signal. For example, the trapeze signal (Fig. 11) follows us the dependence resulted in Fig. 12.

Compression ratio more than 1.5–2 times for the trapeze signal form is inexpedient also due large error.

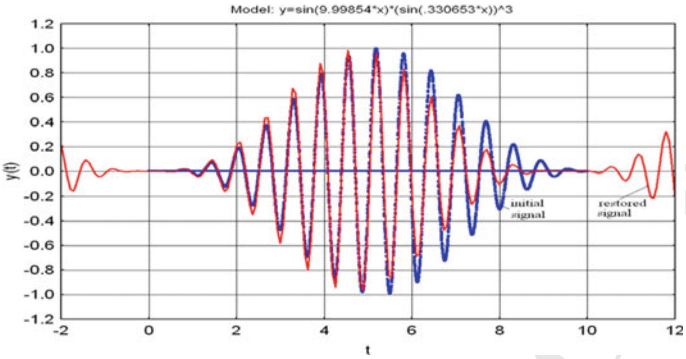

Fig. 10 Signal restoration by N = 5000 samples (red graph)

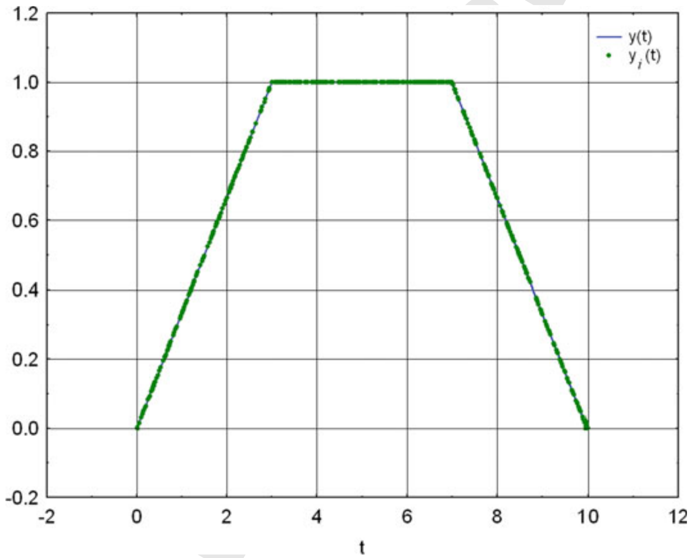

Fig. 11 The signal model

6 Conclusion

Compression of the ultrasonic echo-signal with algorithm based on calculation of the rate of signal change showed better appliance in the wide range of compression ratios (from 1 to 20). Thus, compression ratio k = 20 showed less than 10% value of absolute error and mean square deviation less than 0.02.

Compression algorithm with linear time quantization of ultrasonic signal showed good appliance only for low compression ratios (up to 5). Compression ratio k = 5 showed about 10% value of absolute error and mean square deviation near 0.005.

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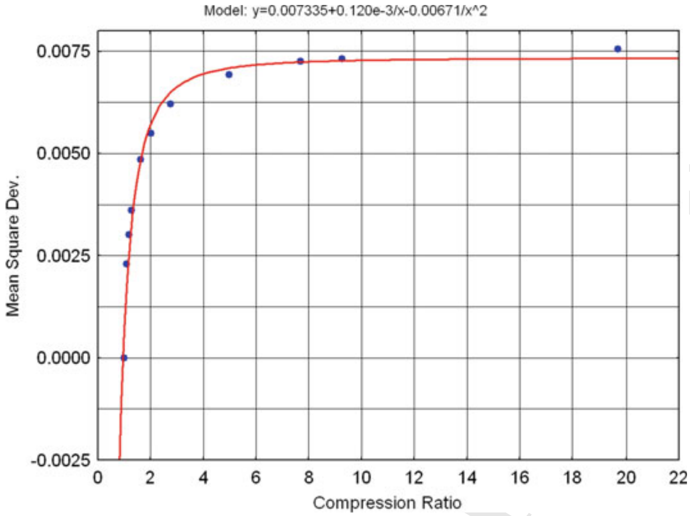

Fig. 12 The mean square deviation for random samples of signal (Fig. 11)

Signal compression with random sampling algorithm showed good rapid increase of mean square deviation for the compression ratios up to 2, but in a wide range of compression ratios (up to 22) mean square deviations does not exceed 0.0075.

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