Compression of Ultrasonic RF data

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Abstract A compression algorithm is presented, which utilizes the special properties of ultrasonic radio frequency (RF) data. The compression is done in two steps: First, linear predictive coding (LPC) is applied, using an one-step-predictor. Further, the remaining error of the prediction is stored using only the necessary word length to store the signal. A lossy extension of the algorithm is presented, which stores only the upper bits of the error signal. The algorithm has been tested with both, data of a speckle phantom and in vivo data. The data could be compressed to approximately 30-55% of the original data size using the lossless algorithm. In comparison, a conventional compression tool achieves 65-75 % of the original data size.

INTRODUCTION

Research and application of many modern ultrasonic imaging and data processing techniques including spatial compounding [4], tissue characterization [5], elastography, and flow measurement require the acquisition of multiple frames of RF echo-data. RF data storage requires a lot of memory. However, many redundancies in the RF data promise a good compression rate for an especially adapted compression technique: The high dynamic range of ultrasonic RF echo data leads to a digital acquisition system with a large number of bits. Hence, in wide areas of the image the amplitudes of the echoes remain below the amplitude range given by the word length of the digital system. Consequently, the upper bits are always zero in these areas. Also, the limited bandwidth implies redundancies within the echo data.

CODING OF RF DATA

Due to the high dynamic range of ultrasonic echo data the amplitude and thus the entropy of the data remains below the possible entropy given by the word length of the digital systems. The entropy H [2,3] of a set of data x_i is given by

$$H = -\sum_{x_i} P(x_i) \log_2 P(x_i) \qquad (1)$$

with $P(x_i)$ being the probability of the samples x_i. H is never larger than the word length b of the digital system. If $H < b$, lossless compression is possible. Using an optimal alphabet, the data size can be reduced by a factor of b/H.

The factor b/H is especially low for acquisition systems in which the RF data are acquired before TGC amplification. Quantitative imaging systems frequently omit the TGC in order to reduce systematic errors. To achieve a specific dynamic range over the entire depth, a larger bit width of the digital system is used in these systems. The limited entropy of the data could be used for compression by coding the RF data with an adapted alphabet, for example a Huffman code [3]. With this alphabet a mean word length which is equal to the entropy can be achieved under optimal circumstances. A major disadvantage of this technique is the dependence of the optimal alphabet from the RF data set. Therefore, either the alphabet has to be stored with the dataset or a sub-optimal global alphabet has to be used.

The RF echo data are known to be approximately Gaussian distributed for short ranges of the RF data [1]. Since the RF echo data is a non-stationary process, the parameters of the distribution will change. In areas with lower echogenicity or, for a system without TGC in larger depths, the variance of the

signal is significantly lower. An example A-scan is presented in Figure 1. This example demonstrates the varying distribution of the RF data in the A-scan. The data was sampled with no TGC applied.
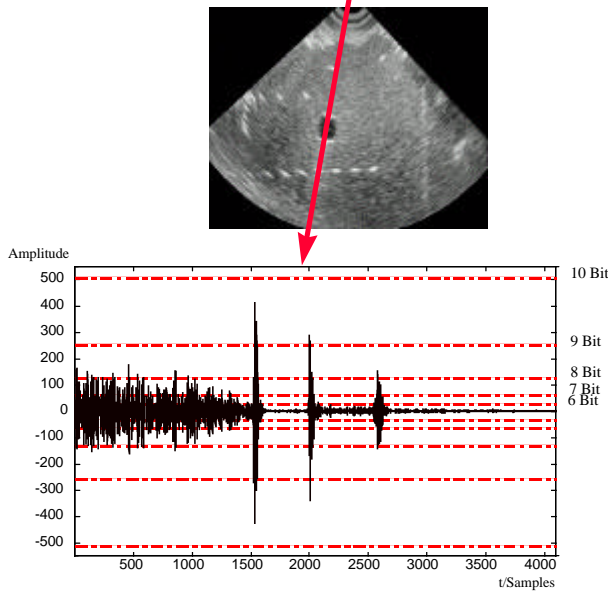
Figure 1. Sample A-scan of a speckle phantom

The knowledge about the amplitude of the echo data being low for large regions within the image can be exploited for the compression algorithm. The data can be stored by adaptively decreasing or increasing the word length depending on the local absolute maximum of the RF data. A typical envelope representing the local maximum is presented in Figure 2. For the reconstruction of this envelope during the decompression, additional code words have to be introduced, which indicate an increase or a decrease of the necessary word length. These code words increase the size of the compressed files and thus worsens the compression. Consequently, the envelope is corrected considering this effect.

Furthermore, the coding algorithm can be extended to a lossy variant, by only storing the upper *n* bits of the data. This reduces the code size of values with high amplitude. Without the lossy extension this values are stored with a higher relative accuracy than values of lower amplitude, which is not necessary in most cases.
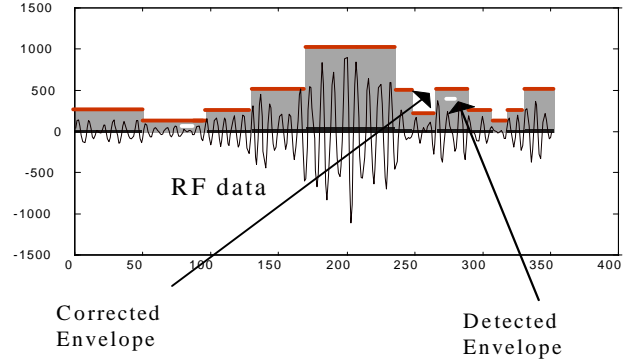
Figure 2. Sample envelope for detection of the necessary word length

LINEAR PREDICTION

Until now, the knowledge about the distribution of ultrasonic RF echo data has been used for compression. Another a priori information about the echo data is its limited bandwidth. In stochastical terms the data is not white noise, meaning previous samples can be used to predict it. We used Burg's algorithm [2,3] to create a one-step-predictor by the use of the correlation properties of the data. The predictor is a IIR-Filter of the order *K*:

$$\hat{x}_l = \sum_{k=1}^{K} a_k x_{l-k} \ . \qquad (2)$$

Burg's estimation of the optimal coefficients a_k always leads to a stable filter [2]. The optimal predictor coefficients are determined for each A-scan and stored in the compressed file. After that only the prediction errors

$$e_l = \hat{x}_l - x_l \qquad (3)$$

instead of the original signal x_l is stored using the coding algorithm described above. The amplitude and hence the entropy of this error is much lower than the entropy of the original signal. Thus the average word length used in the coding algorithm is much lower. The prediction error of the A-Scan of Figure 1 is shown in Figure 3.
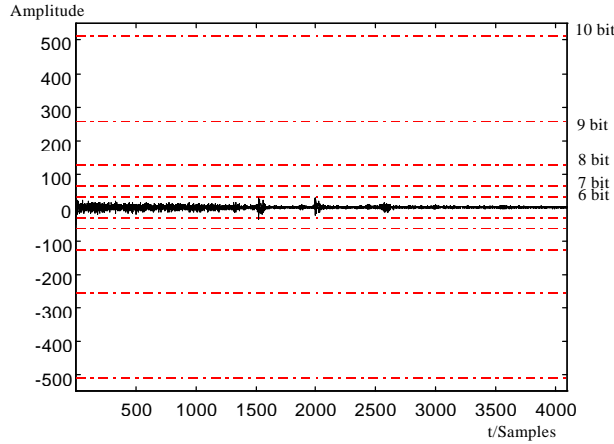
Figure 3. Prediction error of the A-scan from Figure 1

The whole process of compression and decompression with prediction and coding is shown in Figure 4.

Compression
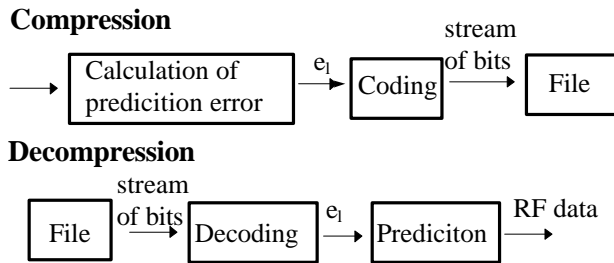

Decompression

Figure 4. Block diagram of the complete compression and decompression algorithm.

A further degree of freedom is the order of the predictor K. There are well known algorithms which estimate the optimal order of the predictor K from the data. In these algorithms the order is searched by minimizing an order criterion, which takes into account the prediction error for an order K. For an optimal predictor in terms of storage effort, a different order criterion has to be introduced which takes into account that an optimal predictor of higher order needs increased header storage which reduces its saving of data storage. However, since these algorithms are time consuming compared to the pure calculation of the optimal coefficients with a given order K, a constant order of $K = 6$ was used, which was found to be nearly optimal for several different data sets.

RESULTS

The compression algorithm has been tested with three different datasets:

a) 12 bit RF data of a speckle phantom with no TGC applied. 11 frames, 107 A-Scans, 4096 samples per A-Scan, center frequency $f_0 = 5$ MHz, 30 MHz sampling rate

b) 12 bit RF data of a human back (in vivo) [4] with no TGC applied. 11 frames, 107 A-Scans, 4096 samples per A-Scan, $f_0 = 5$ MHz, 30 MHz sampling rate

c) 8 bit RF data of a human prostate (in vivo) [5] with a TGC applied. one frame, 281 A-Scans, 2180 samples per A-Scan, $f_0 = 7$ MHz, 33 MHz sampling rate

The success of the compression will be presented by the following ratio r:

$$r = \frac{compressed\ data\ size}{original\ data\ size}. \qquad (4)$$

The use of a lossy compression leads to an error signal s_n. In order to evaluate the quality of the data, a mean local SNR due to these errors is introduced. This SNR is defined as

$$\text{SNR} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum_{m=1}^{M} s_{n-m}^{2}}{\sum_{m=1}^{M} x_{n-m}^{2}}. \qquad (5)$$

This definition calculates the mean value of the SNR's of short ranges of the data. This value can be compared with the quantization error of the digital system. The mean power of the quantization error q_i is

$$s_q^{2} = \frac{1}{N} \sum_{i=1}^{N} q_i^{2} = 0.0833 \qquad (6)$$

assuming an equal random distribution of these errors. An ideal adapted sine wave has a power of

$$P = 2^{2b}/2 \qquad (7)$$

introducing the bit width b of the digital system.

This leads to the maximal SNR of

$$SNR_{max} = 10\log_{10}(0.166/2^{2b}) \ . \ (8)$$

If the mean local SNR of Equation (7) is compared to the maximal SNR_{max} of the acquisition system, we get a worst case guess (the echo data does not have the power of the ideal adapted sine wave of Equation (8)) of the effect of lossy compression on the SNR. Since the SNR in Equation (7) is a mean value of a *local* SNR, the SNR does only have to be large enough to cover the dynamic range of the backscattering, and not the effects of the attenuation. In Table 1-3 the compression ratios and the SNR of lossy and lossless compression of the three data sets are compared. The compression ratio which were achieved with the standard packer program „ZIP" is presented in these tables, too. In most cases the dynamic range of the lossy compression should be large enough to cover the dynamic range of the backscattering.

kind of comp.	ratio r	SNR
lossless	42 %	max. 74 dB
max. 8 bit	38 %	56 dB
max. 6 bit	33 %	42 dB
Zip	63 %	max. 74 dB

Table 1: compression of dataset a)

kind of comp.	ratio r	SNR
lossless	42 %	max. 74 dB
max. 8 bit	37 %	58 dB
max. 6 bit	33 %	43 dB
Zip	54 %	max. 74 dB

Table 2: compression of dataset b)

kind of comp.	ratio r	SNR
lossless	29 %	max. 50 dB
max. 6 bit	29 %	37 dB
max. 6 bit	26 %	35 dB
Zip	40 %	max. 50 dB

Table 3: compression of dataset c)

CONCLUSION

An algorithm has been developed that utilizes the special properties of ultrasonic RF data for compression. The achieved compression ratios by our algorithm exceeds the results from conventional packer programs significantly. It has been demonstrated with both, phantom and in vivo data, that the RF data can be compressed to about 30-40 % of the original size.

ACKNOWLEDGMENTS

REFERENCES

[1] R. F. Wagner, S. W. Smith, J. M. Sandrik and H. Lopez, "Statistics of Speckle in Ultrasound B-Scans," *Trans. Sonics Ultrason*., vol. 30 pp. 156-163, 1983

[2] A. Papoulis, *Probability, Random Variables, and Stochastic Processes*. New York: McGraw-Hill, 1991

[3] W.H. Press, S.A. Teukolsky, W. T. Vetterling, B.P. Flannery, *Numerical Recipes in C*, Cambridge: Cambridge Univerity Press, 1992

[4] A. Pesavento, H. Ermert, J. Grifka, E. Broll-Zeitvogel, "Ultrasonic Reflection Tomography of Post-Discotomic Scarring", *Acoustical Imaging 23*, in press, New York: Plenum Press

[5] G. Schmitz, H. Ermert, T. Senge, "Color-coded tissue characterization images of the prostate", *Acoustical Imaging 22*, pp. 359-364, New York: Plenum Press, 1996