NEW ASSESSMENT SYSTEM FOR DATA COMPRESSION IN ULTRASOUND COMPUTER TOMOGRAPHY

R. Liu, N. V. Ruiter, M. Zapf, R. Stotzka, M. Weber, H. Gemmeke,
Institute of Data Processing and Electronics at Forschungszentrum Karlsruhe
Hermann-von-Helmholtz-Platz 1, 76344 Leopoldshafen
Germany
liu@ipe.fzk.de

ABSTRACT
This paper proposes a comparison method for various compression techniques for medical imaging systems. The quality of images reconstructed with compressed datasets is used to score the compression process. The image quality is measured by mutual information between a reference and the reconstructed images. Six lossy compression methods, ranging from simple thresholding to discrete wavelet based compression methods were used to compress ultrasound signals over a large range of compression ratios. Experimental results with simulated ultrasound computer tomography system show the influence of compression on datasets is properly measured by mutual information. The possible utilization of the assessment system is discussed.

KEY WORDS
Data compression, image quality, ultrasound.

1. Introduction

At Forschungszentrum Karlsruhe 3D Ultrasound Computer Tomography (USCT) for breast cancer screening is under development [2]. About 20 GBytes of raw data are accumulated for one breast volume. In order to facilitate data transmission, storage and reconstruction process, the amount of data has to be reduced considerably by a lossy compression method. Although hundreds of data compression methods exist, an unsolved problem is how to measure the effect of different compression methods on the quality of images for the end user [1], e.g. radiologists.

To assess the quality of compression methods for ultrasound dataset, the 'state of the art' method takes the original dataset as reference [6]. The original datasets contain not only the information for image reconstruction, i.e. amplitude and Time-of-Arrival (TOA) but also many distortions, e.g. noise and redundancies (details see section 2). Because of the influence of distortions, the image reconstructed with the original dataset is degraded. With a low quality image as reference, the evaluation results of compression methods might not give proper evaluation results. Hence an evaluation method to score the compression methods has to be found.

The purpose of this work is to develop a metric for determining the influence of various compression algorithms on the quality of 3D USCT images. The ultrasound signal measured by certain combination of emitter and receiver transducers is named A-Scan. The compression methods are used to the A-Scans of ultrasound datasets to reduce the applied amount of data. Then the compressed datasets are used to reconstruct images. With the same reconstruction process, the quality of a reconstructed image depends only on the quality of datasets; therefore an obvious idea of assessing data compression is the comparison of the quality of reconstructed images for the different compression methods.

The advantages of an image quality based assessment system are obvious for a medical imaging system. The information content of a whole dataset is transferred to the end user only by the reconstructed images. High quality of an image is usually the aim of a medial imaging system. At the same time, measuring the quality of one image is much simpler than that of millions of single signals.

In Section 2, basic construction of the assessment system is presented. The details of implemented compression methods and image quality measurement are described in the following subsections. The designed experiment with the simulated USCT setup can be found in Section 3. Results of experiment are analyzed in Section 4. The performance and generalization of the method are discussed in Section 5.

2. Assessment System

The information for image reconstruction in A-Scans is amplitude and TOA of scattered ultrasound pulses. The ideal image, i.e. reference image, is reconstructed with ultrasound pulses carrying only this information content. This ideal image is the best image which can be achieved by USCT. The pulse shape of transducer signals is fixed by the applied center frequency, bandwidth, and impulse response of sensors. An analysis of the relationship between ultrasound pulses and reconstructed images in USCT is demonstrated in Fig. 1.

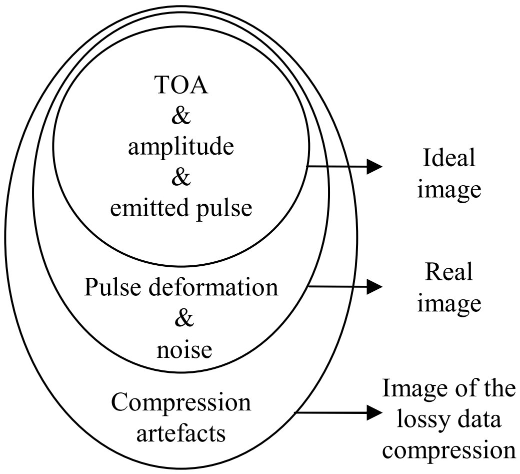


Fig. 1. Relationship between reconstructed images and characteristics of ultrasound pulses.

The real ultrasound pulses are affected by deformation and noise, which is considered as distortions for reconstruction of a high quality image. The deformation results from the attenuation and dispersion in the media [14]. Complex objects might cause different deformation of ultrasound pulses depending on the path of the wave taken through the objects [2].

Data compression influences not only the information content but also irrelevant contents in signals. The assessment system should measure the quality variation of compressed datasets due to the compression artefacts, where only reduction of information content should be punished.

The assessment strategy is demonstrated with the flowchart in Fig. 2.

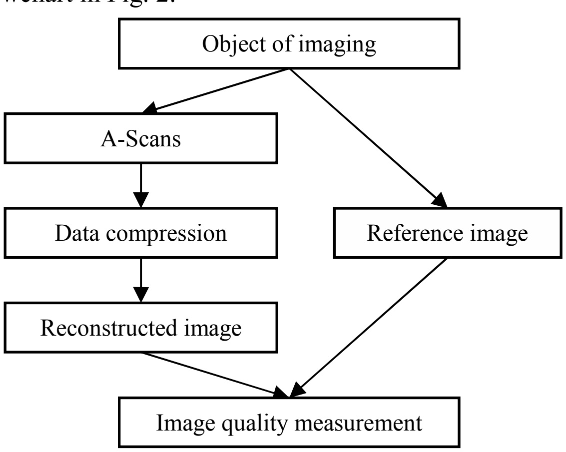


Fig. 2. Basic schema of the assessment system.

All the ultrasound signals, i.e. A-Scans, are compressed and then used to reconstruct an image. At the same time, the reference image is generated. The image quality of the compressed image is assessed by comparing it with the reference image, i.e. the ideal image. Details of the comparison are given in the next sections.

2.1 Lossy Data Compression

Lossy data compression was adopted to achieve a high compression ratio. The lost information can not be restored; therefore only the noisy and redundant information should be removed. The main structure of a compression process is shown in Fig. 3.

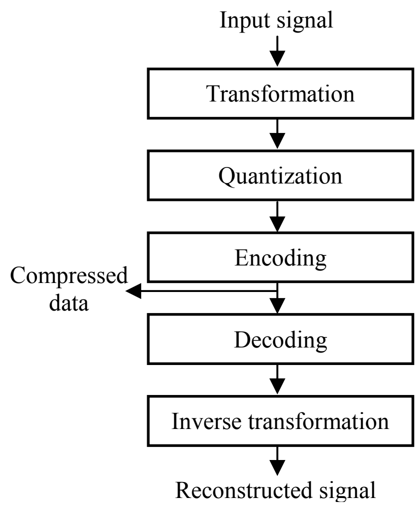


Fig. 3. Compression algorithm.

The aim of using a transformation in a compression algorithm is to represent the information content in A-Scans with relative higher amplitudes to irrelevant contents. The redundancy, noise and distortions are expected to be removed by the quantization techniques. Encoding should save the remaining information in the most compact format.

The characteristics of the received ultrasound pulse P_r can be described by:

$$P_r(t) = A * \hat{f}(t) * \delta(t-\tau) + n . \qquad (1)$$

Where A and τ are the amplitude and the TOA. δ denotes the time delay function and n the noise. $\hat{f}(t)$ describes pulse shape of the received signal at the time t. The shape of $\hat{f}$ is strongly related to pulse shape of the emitter, which is known from calibrations; thus waveform based transformations, such as discrete wavelet, multifractal, and deconvolution were implemented. Additionally, two compression methods based on peak detection were used for comparison.

- **Wavelet:** Each A-Scan is transformed to a sequence of wavelet coefficients with the discrete wavelet transformation (DWT) [5]. DWT employs a standard mother wavelet, i.e. Symmlet, whose shape is similar to the emitted ultrasound pulse. The wavelet coefficients are quantized and encoded with hard thresholding and run length encoding methods (RLE). For reconstruction of images A-scans are recovered from the compressed wavelet coefficients by inverse DWT.

- **MultiFractal:** The difference between wavelet and multifractal is that the wavelet coefficients of high frequencies are damped, since they contain little information of A-Scans. The relationship between fractal, multifractal, and wave methods can be found in [3].

- **DCV:** Spiking deconvolution filter is derived from the emitted ultrasound pulse. The amplitude and time position of a pulse, which has the same shape as the emitted pulse, is represented by a peak in an A-Scan filtered with a spiking deconvolution filter [4]. DCV is similar to Wavelet, except replacing the wavelet transformation by filtering with the known emitted pulse.

- **IKstd:** The points of the largest amplitude [10], i.e. peak, within a local neighborhood are detected in each A-Scan. A hard thresholding method is used before peak detection. The size of the local neighbourhood [16] is fixed and adapted to the shape of the emitted pulse. The position and amplitude of each peak are saved as compressed data.

- **IK:** In contrast to IKstd, the size of the local neighbourhood increases to achieve high compression ratios in IK.

- **Threshold:** With the hard thresholding method A-Scans are quantized without transformation [14].

2.2 Reconstruction

The designed assessment system is independent of a reconstruction method, since the comparison of different compressed dataset is based on the same reconstruction method.

2.3 Image Quality Measurement

During the past twenty years, mutual information became popular for medical image registration [7]. A frequently used term is Average Mutual Information (AMI). It is given by the following equation:

$$AMI(A,B) = H(A) + H(B) - H(A,B)$$

Where $H(A)$ and $H(B)$ are the Shannon entropy of image A and B; $H(A,B)$ means the Shannon entropy of the joint histogram, i.e. two-dimensional histogram of the grey level combinations occurring at same image positions. AMI is used here to measure the degradation of datasets caused by the compression processes by comparing the resulting image to the reference image.

3. Experiment with Simulated USCT

The advantage of a simulated version of USCT is that the acoustic parameters and the position of objects can be set precisely, thus an accurate reference image can be created. The compressed dataset can then be measured by comparison with the accurate reference image. In the simulated pulses only the influence of deformation are considered. The addition of noise to simulated datasets will be carried out in the next step of research. Compared to simulated datasets, real dataset with available phantom geometry has the disadvantage of uncontrollable noise, imprecise absolute position of the phantom in the USCT and difficulties to measure the acoustic parameters precisely. The aim of the experiments is to analyze the image quality for different compression ratios by the use of AMI.

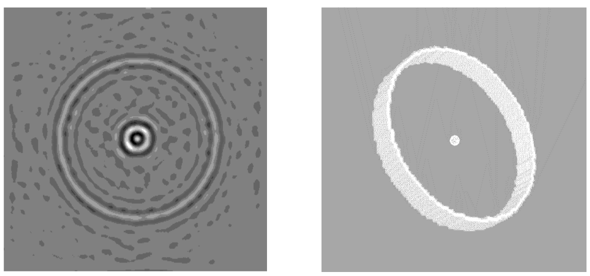
3.1 Experiment Design

The simulated dataset was generated with predefined parameters and a working process similar to USCT described in [11]. Wave propagation is simulated by solving the wave equation with finite difference method [8] in Wave3000, which is an ultrasound simulation software provided by CyberLogic, Inc. [12].

The object to be imaged consists of breast tissue with microcalc deposits. Materials with similar acoustic properties as breast tissue, e.g. blood or fat, were adopted for the simulation. In this experiment object was simplified with a model consisting of a blood cylinder and a bone sphere. The object is immersed in water as coupling medium. Because of the limitation of simulation time and memory, the size of the blood cylinder was scaled down to 10% of a real breast, i.e. approximate 10 mm and the diameter of the bone sphere is 0.2mm. Then the simulation process takes about 10 days with one PC (Pentium 4, 3.2 GHz, 2.0 GB RAM). The applied ultrasound pulse had a center frequency of 1 MHz. The attenuation parameters for all materials are based on 1 MHz. Signals from combinations of 96 emitting and 192 receiving transducers were used to reconstruct images with a resolution of 1421 dpi, i.e. 56 Pixel/mm. Before reconstruction, the signals were compressed at 20 different compression ratios from 0 to 897 with the six methods given in section 2.1. The reconstructed image without compression is shown in Fig. 4(a). The contour of the blood cylinder and the bone sphere can be seen clearly.

3.2 Reference Image

Due to the use of reflection imaging in USCT for reconstruction, the reference image depicts the contours of the objects. The reflectivity coefficient is based on the difference of acoustic impedances between media. The gradient of the acoustic impedances is normalized and set as the grey level of object contours in the reference image. The Laplacian image filter from the image processing toolbox of MATLAB [15] was employed to calculate the gradient of the acoustic impedance. In order to equate the scale of the reference images and the reconstructed images, the geometry of the objects is drawn by the Bresenham algorithm [9]. Fig. 4(b) depicts the reference image with the same resolution as reconstructed images. The relative position of the bone sphere to the blood cylinder is illustrated in Fig. 4(b). For the transmission tomography, the reference image should be designed based on the absorption coefficients of media



(a) **(b)**

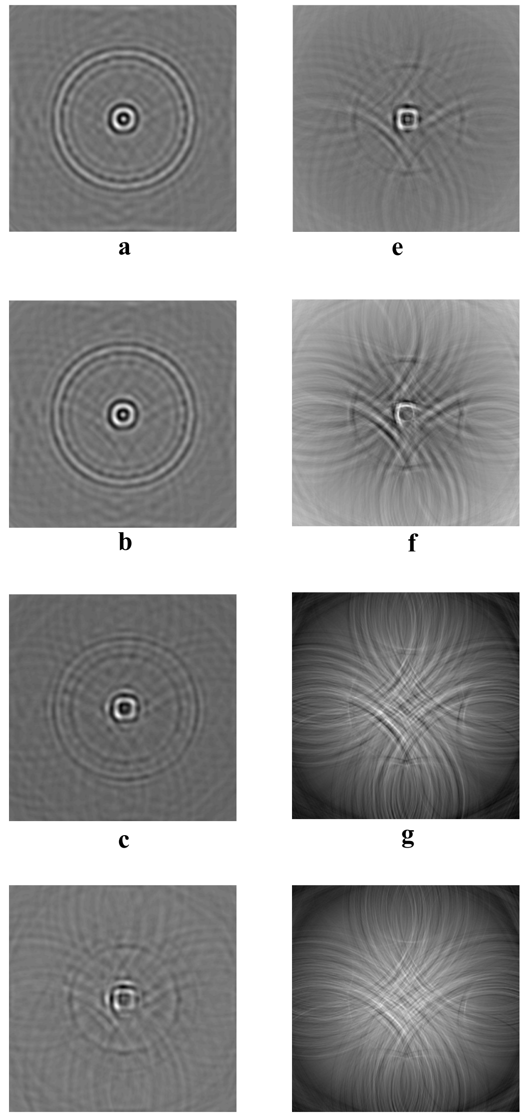
Fig. 4. One slice of image reconstructed with uncompressed ultrasound signals (a) and the 3D reference image (b). In the middle a bone sphere is surrounded by a blood cylinder.

4. Result and Performance Evaluation

For each compression method, as displayed in Fig. 5-7, it can be observed that the borders of objects become blurred with increasing compression ratio.

At the same compression ratio, Wavelet, MultiFractal, IKstd and IK methods show better performance than DCV and Threshold methods. Wavelet and MultiFractal methods use localized information simultaneously in time and frequency domain [5]. The selected mother wavelet, i.e. Symmlet, for Wavelet and MultiFractal is similar to the emitted ultrasound pulse. Therefore the information content can be separated well from irrelevant parts of datasets and is maintained during compression process.

Since the distance (roughly 10 mm) between the reflected ultrasound pulses from the border of the blood cylinder and the bone sphere is much larger than the wavelength (1.5 mm), the two reflected pulses do not interfere with each other as for most cases. IKstd and IK methods are suitable to identify well separated peaks in the signal. For a simple object and a low level of noise in dataset, IK and IKstd are recommended for good performance of compression. Although DCV uses a deconvolution filter derived from the emitted ultrasound pulse, the high sensitivity of the deconvolution filter to pulse deformation limits the utilization of the DCV method.



d **h**

Fig. 5. Each image shows for the same simulated dataset the same reconstructed slice after compression with Wavelet (a, b, c, d) and Threshold (e, f, g, h) at compression ratios of 10, 20, 60, and 100.

Finally, the quality of the reconstruction is measured with AMI in Fig. 8. As main tendency the AMI values decrease with increasing compression ratios. Between the range of compression ratios from 0 to 30, IKstd, Wavelet, MultiFractal, and IK method have larger AMI than Threshold and DCV method. At compression ratios above 20, reconstructed images were distorted significantly. These results demonstrate that the scores of AMI are

consistent with the subjective observation of image quality.
Additionally, with the Wavelet and IKstd method, the AMI at a compression ratio of 15 is 3% larger than the AMI for the uncompressed data. In the simulation the emitted pulse shape is deformed due to the applied materials.

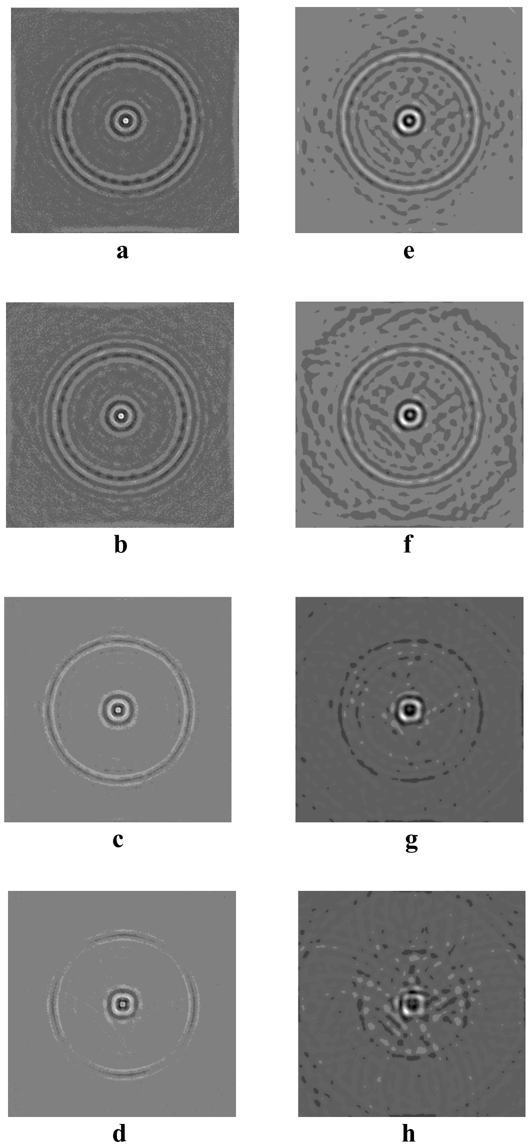


Fig. 6. As Fig. 5 for compression with IKstd (a, b, c, d) and MultiFractal (e, f, g, h) at compression ratios of 10, 20, 60, and 100.

Note, the experiment results in Fig. 8 with a compression ratio smaller than one are due to the low performance of the encoding method, e.g. RLE, for the A-Scans with very few repeated samples. In these cases compression is not necessary.

5. Discussion and Conclusion

By the use of Wavelet and IKstd methods, the reconstruction gets less sensitive to deformations. In the experiment, the IKstd method shows a higher AMI than the Wavelet method because of the simple structure of the designed object. Further experiments will study the performance of all methods for complex objects.

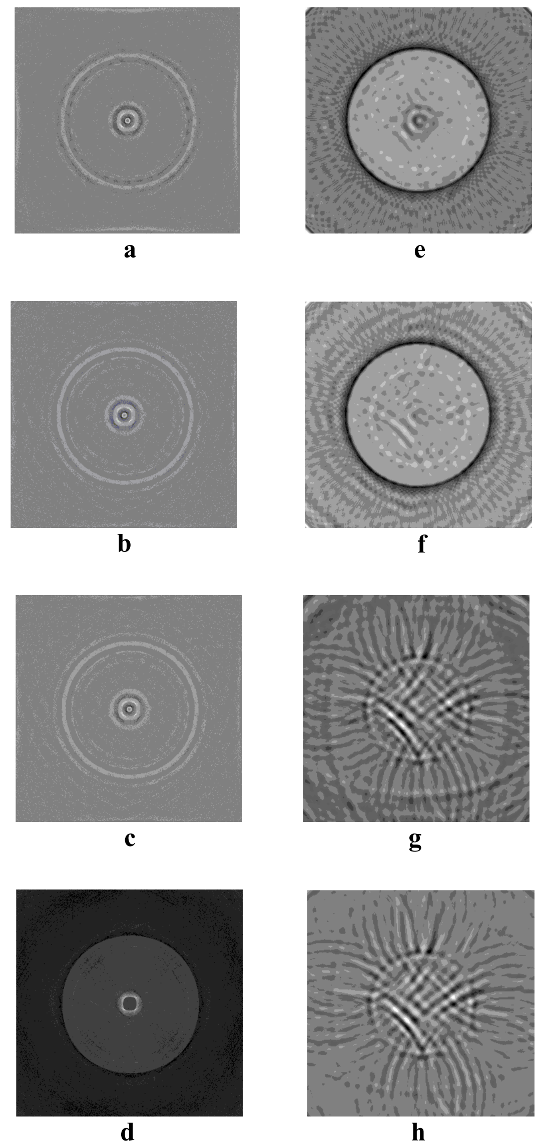


Fig. 7. As Fig. 5, 6 for compression with IK (a, b, c, d) and DCV (e, f, g, h) at compression ratios of 10, 20, 60, and 100.

The local maximum of the AMI curve indicates that the compression process can improve the image quality. This local maximum is expected also to appear in noisy datasets, since a suitable compression method should be able to keep the information content but reduce the noise. The positive influence of the compression process reaches its maximum at the optimal compression ratio. After that maximum the information content is decreased. The hypothesis is that the maximum of the AMI curve is helpful to achieve an optimal compression ratio for USCT.

The experiments were carried out with simulated USCT data in order to get precise reference images. If an accurate reference image is available, this system may be used to evaluate the compression performance for real noisy ultrasound datasets in the future work.

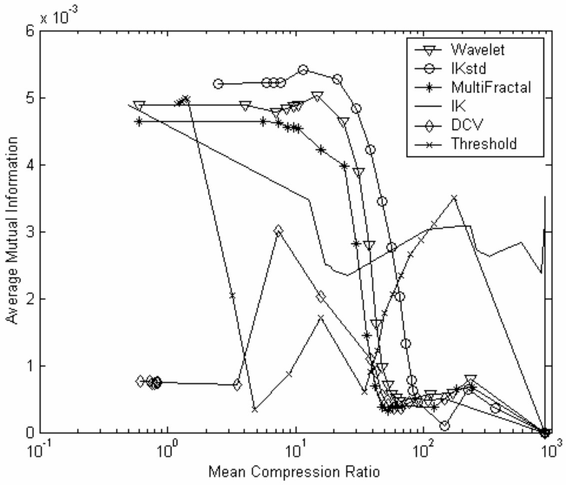


Fig. 8. Assessment of different compression methods with average mutual information between reference image and reconstructed image with compressed signals.

For a practical use of the compression methods with 20 GBytes of raw data, the computational complexity of the method is also important, e.g. the compression and decompression should not exceed the data reconstruction time. For future applicability a tradeoff between image quality and computational complexity has to be found.

In conclusion a novel assessment system based on the quality of reconstructed images was successfully developed for data compression in USCT. The system demonstrates the influence of compression on the quality of datasets and is appropriate for USCT. Also the effect of noise filters on the image quality may be measured.

Furthermore, this system is also suitable for evaluation of data compression in other imaging technologies, e.g. conventional ultrasound imaging for medical and non-medical applications.

References

[1] J. Kerekes, Image Data Compression, available at http://www.grss-ieee.org/menu.taf?menu=Resources&detail=include&html=IFTKerek2, 1995.

[2] N.V. Ruiter, et al., 3D ultrasound computer tomography: results with a clinical breast phantom. *IEEE International Ultrasonics Symposium, Vancouver, Canada,* 2006.

[3] L. J. Vehel, Wavelet-based multifractal methods in image processing. *18th international Conference on Pattern Recognition,* Hong Kong, 2006.

[4] Z. Yao, Optimal time-delay spiking deconvolution and its application in the physical model measurement. *CREWES Research Report, 11*, 1999.

[5] A. Graps, An Introduction of Wavelets. *IEEE Computational Science and Engineering, 2*, 1995.

[6] G. Cardoso, J. Sanlle, Ultrasonic data compression via parameter estimation, *IEEE Transaction on Ultrasonics, Ferroelectrics and Frequency Control, 52*(2), 2005.

[7] J. P. W. Pluim, J. B. A. Maintz & M. A. Viergever, Mutual information based registration of medical images: a survey, *IEEE Transaction on Medical Imaging, XX*(Y), 2003.

[8] P. P. Delsanto, R. S. Schechter & R. B. Mignogna, Connection Machine Simulation of Ultrasonic Wave Propagation in Materials III: The Three-Dimensional Case, *Wave Motion, 26*, 1997, pp 329-339.

[9] J. E. Bresenham, An incremental algorithm for digital plotting, *ACM National Conference,* Denver, Colorado, 1963.

[10] M. Balzer & H. Stripf, Online data reduction system with DSPs, *6th International Symposium on Signal Processing and its Applications,* Kuala Lumpur, Malaysia, 2001.

[11] M. Weber, et al., Ultraschallsimulation für die Ultraschall-Computertomographie, *Workshops Bildverarbeitung für die Medizin*, 2006.

[12] CyberLogic, Inc., available at http://www.cyberlogic.org/wave3000.html, 1997-2006.

[13] D. Salomon, *A guide to compression methods* (New York: Spring-Verlag, 2002).

[14] P. M. Morse & K. U. Ingard, *Theoretical acoustics* (Princeton: Princeton University Press, 1987).

[15] The MathWorks, Inc., available at http://www.mathworks.com, 1994-2006.

[16] R. M. Cramblitt, et al., Ultrasound image compression exploiting image formation modles. *IEEE International Ultrasonics Symposium, San Antonio, TX, USA,* 1996.