Decomposition-Based Compression of Ultrasound Raw-Data

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Abstract. Sonography techniques use multiple transducer elements for tissue visualization. The signals detected at each element are combined in the process of digital beamforming, requiring that large amounts of data be acquired, transferred and processed. One of the main challenges is reducing the data size while retaining the image contents. For this purpose, we propose a component based model for the raw ultrasonic signals. We show that a decomposition based approach with a suited processing scheme for each component individually, can achieve over twenty-fold reduction of needed data size.

Keywords: Biomedical ultrasound · Signal modeling · Sparse representation · Dictionary learning

1 Introduction

Medical ultrasound imaging allows visualization of internal body structures by radiating them with acoustic energy and analyzing the returned echoes. The two-dimensional image typically comprises of multiple one-dimensional scan lines, each constructed by integrating the data collected by the transducer elements following the transmission of an acoustic pulse along a narrow beam. As the transmitted pulse propagates through the body, echoes are scattered by acoustic impedance perturbations in the tissue. These back-scattered echoes are detected by the transducer elements and combined, after aligning them with the appropriate time delays, in a process referred to as beamforming, which results in Signal-to-Noise Ratio (SNR) enhancement. Each resulting beamformed signal forms a line in the image.

Taking into account the high frequency used for ultrasound imaging, the number of transducer elements and the number of lines in an image, the amount of data needed to be transferred and processed is very large, motivating methods to reduce the amount of needed data without compromising the reconstructed image quality and its diagnostic credibility. In recent years, there has been growing interest in reducing the amounts of data in general signal processing applications, and significant research efforts have been focused at the field of sparse

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representations and Compressed Sensing (CS) [9,10]. Ideas arising from CS theory have been successfully implemented in diverse applications such as radar [3,5], Synthetic Aperture Radar (SAR) [17,20], and MRI [16].

Several preliminary works have recently adapted these methods to ultrasound signals [4,11–15,18,19,21].

Another set of works attempting to reduce the amount of sampled data in ultrasound signals, based on complementary ideas arising from the Finite Rate of Innovation (FRI) framework [6,25], was carried out by Tur et al. [24] and later extended by Wagner et al. [26].

The authors modeled the ultrasonic echo as a finite stream of strong pulses, which are replicas of a known-shape pulse with unknown time-delays and amplitudes:

$$x(t) = \sum_{\ell=1}^{L} a_\ell h(t - t_\ell) \tag{1}$$

Assuming that overall L pulses were reflected back to the transducer from the pulse's propagation path, the detected signal is completely defined by $2L$ degrees of freedom, corresponding to the unknown parameters $\{a_\ell, t_\ell\}_{\ell=1}^{L}$. Based on the FRI framework, these $2L$ parameters are estimated and the signal recovered from a minimal subset of $2L$ of the signal's Fourier series coefficients. The needed coefficients are recovered from low rate samples of the analog signals, as the sampling frequency is now determined by the number of pulses L, which is rather small compared with the bandwidth of the transmitted pulse, leading to a substantial sample rate reduction.

These works achieve an almost eight-fold reduction of sample rate, however the reconstructed data is partial as it only contains the macroscopic reflections while disregarding the speckle.

As the focus of our work, we aim at reducing the large amount of data needed to be stored and processed while preserving the image contents including the speckle.

Our proposed digital processing scheme is based on the separation of the received ultrasonic echoes into two components, both carrying valuable information: the strong reflectors component, that is highly important for tracking purposes in cardiac ultrasound imaging [7,23], and the speckle, also referred to in this work as the background component, that characterizes the microscopic structure of the tissue [8].

We then show that each component on its own is compressible, and derive the suitable representation bases. Thereafter, the compressed background signals are integrated in a digital beamforming process. To conclude the proposed algorithm, the strong reflectors may be reconstructed from their sparse coefficients obtained during the decomposition stage, combined with the beamformed background signals and processed to form an image.

Applying the proposed processing schemes to real cardiac ultrasound data, we successfully reconstruct both macroscopic and microscopic reflections from the scanned region, such that the image contents are highly preserved, while achieving over twenty-fold reduction of the data size.

Throughout this paper, we use the term *raw signals* to refer to the ultrasonic signals detected by each sensor immediately after their sampling.

2 Signal Decomposition

As previously stated, each received signal x is initially decomposed into a background signal x_b and strong reflectors component x_s. The decomposition algorithm is based on a greedy detection of the strong reflectors followed by their separation from the original signal.

Modeling the strong reflectors component, we mostly adopt the "stream of pulses" signal model [24,26] according to which this component is composed of a limited number of strong pulses, that are amplified and delayed replicas of a known-shape pulse (1). This pulse $h(t)$ has the form of a sinusoid signal oscillating at the transmission frequency f_0 in a Gaussian envelope.

As an extension to this model, we suggest that the returning pulse shape is somewhat corrupted with respect to the transmitted pulse. This corruption may be manifested in either a frequency shift, resulting from the frequency dependent attenuation [2], or a phase shift formed between the carrier wave and the Gaussian envelope. In order to account for those possible corruptions, we propose to represent the strong reflectors in a time-frequency domain using the Short-Time Fourier Transform (STFT). This will allow simultaneous optimization of both the time-delay and frequency shift.

Denoting the STFT of $x(t)$ by $\mathbf{X}(t, \omega)$, the STFT decomposition is

$$\mathbf{X}(t,\omega) = \mathbf{X_b}(t,\omega) + \mathbf{X_s}(t,\omega) = \mathbf{X_b}(t,\omega) + \sum_{k=1}^{L} a_k \mathbf{H}(t - t_k, \omega - \omega_k) \qquad (2)$$

The proposed decomposition algorithm is described in Algorithm 1.

In the presented algorithm, the strong reflectors are detected as the maximal magnitude peaks of the STFT. In practice, the detection can be improved by matching the known pulse pattern in a narrow region around each peak. The maximal number of pulses L and error threshold ϵ_0 are chosen empirically.

It can be observed that the strong reflectors are naturally compressed by saving only the pulse model parameters $\{a_k, t_k, \omega_k\}_{k=1}^{L}$ along the decomposition process. This may be thought of as sparse coding over a very large dictionary whose atoms represent all the possible time and frequency shifts of the known pulse. However, due to the high sampling rate of the signals and the enormous dimensions of such dictionary, standard OMP-like techniques are not feasible and an alternative amplitude-based pulse matching was here performed.

3 Background Data Compression

Resulting from intereferences of weak ultrasonic reflections, speckle is typically characterized by a statistical model with few parameters, indicating that it could

Algorithm 1. STFT-based Decomposition

Task: Decompose a given signal x into the strong reflectors and background components (x_s, x_b respectively)
Inputs: The signal's STFT $\mathbf{X}(t,\omega)$, the STFT signature of the pulse model $\mathbf{H}(t,\omega)$ centered such that $\arg\max\limits_{(t,\omega)}|\mathbf{H}(t,\omega)| = (0,0)$, the maximal number of pulses L, and an error threshold ϵ_0.
Initialization: Set the initial residual $\mathbf{r^0} = \mathbf{X}(t,\omega)$
Main Iteration: for $k = 1, ..., L$ perform the following:

– Locate the strongest reflection (t_k, ω_k) with magnitude a_k:

$$(t_k, \omega_k) = \arg\max_{(t,\omega)}|\mathbf{X}(t,\omega)| \quad ; \quad a_k = \mathbf{X}(t_k, \omega_k)$$

– Residual update: $\mathbf{r^k} = \mathbf{r^{k-1}} - a_k\mathbf{H}(t - t_k, \omega - \omega_k)$
– Stopping Rule: If $\|\mathbf{r^k}\|_\infty < \epsilon_0$, stop. Otherwise, apply another iteration.

Output: $x_s(t) = ISTFT\left(\sum_{j=1}^{k} a_j\mathbf{H}(t - t_j, \omega - \omega_j)\right)$, $x_b(t) = ISTFT(\mathbf{r^k})$.

be easily sparsified. Having separated the two components, and considering that the strong reflectors are readily compressed, we next want to compress the background component as well.

For that purpose, each such background signal will be sparsely represented over an optimized dictionary that is trained offline from prototype examples using the K-SVD algorithm [1]. For the training set we use a small, randomly-chosen subset of the signals constituting a single frame of real cardiac imaging data, each of them divided into one-dimensional, non-overlapping patches. Although our goal is to compress raw signals, i.e. signals detected by each sensor prior to receive beamforming, the training set signals are chosen to be beamformed scan lines, since those were shown to have improved SNR [22].

It should be emphasized that the aforementioned dictionary learning process is only performed once for every imaging system settings, and do not need to be repeated for every analyzed signal or even for every imaged frame.

Returning to the online processing cycle, each separated background component is next divided into non-overlapping patches and sparsely represented over the trained dictionary.

Denote by $\boldsymbol{\varphi}_m \in \mathbb{R}^N$ the background component of the signal received by the m-th sensor. Each such component is divided into P patches $\mathbf{y}_{m,p} \in \mathbb{R}^Q$ of length Q:

$$\boldsymbol{\varphi}_m = \left[\mathbf{y}_{m,1}^T \; \mathbf{y}_{m,2}^T \cdots \mathbf{y}_{m,P}^T\right]^T \tag{3}$$

Denote the dictionary by $\mathbf{A} \in \mathbb{R}^{Q\times K}$ ($K > Q$), then using Orthogonal Matching Pursuit (OMP) we solve for each patch ($\forall 1 \leq m \leq M, 1 \leq p \leq P$)

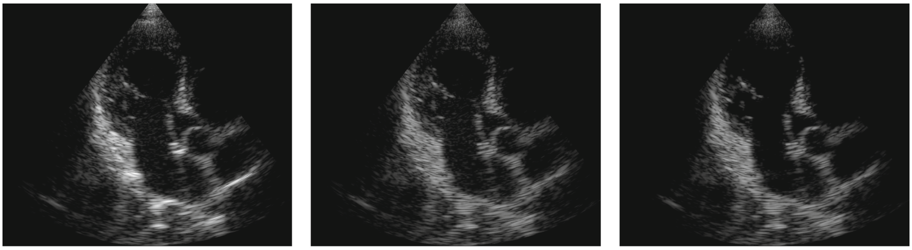
$$\arg\min_{\mathbf{z_{m,p}}} \|\mathbf{z_{m,p}}\|_0 \quad \text{subject to} \quad \|\mathbf{A}\mathbf{z_{m,p}} - \mathbf{y_{m,p}}\|_2 \leq \epsilon \tag{4}$$

Following, each patch is reconstructed by $\hat{\mathbf{y}}_{m,p} = \mathbf{A}\mathbf{z}_{m,p}$ and the recovered patches are plugged back to reassemble the full signals $\{\boldsymbol{\varphi}_m\}_{m=1}^{M}$. Afterwards, these signals are combined to produce the beamformed background signal, which could then be further processed to form the image. Moreover, we note that a simplified beamforming process may be carried out in the representation domain, as a weighted combination of the sparse representation coefficients. The weights are data independent and can be pre-computed, so that only the sparse coefficients should be transferred to the beamformer.

4 Simulation and Results

Our proposed method was evaluated on several sets of consecutive frames of cardiac ultrasound data provided by GE Healthcare.

The results obtained for a typical frame are illustrated in Fig. 1. The original frame is presented along with the corresponding background estimation and its 24-fold compressed version.



(a) (b) (c)

Fig. 1. Background estimation and compression results. (a) Original image. (b) STFT background image. (c) Compressed STFT background image (PSNR = 29.16[dB]).

It can be observed that the proposed decomposition successfully detects and removes the strong reflections, producing a background image with relatively homogeneous regions. Moreover, the compression scheme produces a visually good image that preserve even the subtle image features. These results were obtained despite the formerly mentioned challenges, and while achieving a compression ratio of 24.56, implying that the number of coefficients needed for reconstruction is only 4 % of the number of time samples in the received RF signal.

Similar results were obtained for other cardiac ultrasound frames and for computer simulated phantoms.

Recall that the dictionary used for sparse coding was learned from a subset of a single frame, yet our results indicate that it is suitable for representing data of other frames obtained with the same imaging settings (not necessarily from the same consecutive set as the image used for training).

Comparing our decomposition-based compression with a direct compression of the raw signals, that was performed using a similar K-SVD dictionary learning approach, we found that in order to obtain a compressed image of comparable quality in terms of the visible amount of saved features, a compression factor of only 10.99 was obtained in the direct compression.

In this regard, it should be pointed out that for analyzing the total amount of saved data, a fair comparison demands that the amount of coefficients needed for representing the strong reflectors is added to those used for representing the background signal. By doing so, a slightly reduced compression ratio of 21.4 is achieved. Nonetheless, this achieved compression ratio is still twice as high as the one achieved for the original raw data.

Moreover, assuming a known pulse shape, the strong reflectors reconstruction is straightforward and does not require beamforming or any additional processing. Therefore, in terms of the data needed to be employed in beamforming computations, the higher compression factor (that only considers the background) is still applicable.

The decomposition-based compression is thus significantly advantageous to a direct compression of the raw data in terms of the achieved compression ratio.

5 Conclusions

In this work, we extended previous models proposed in [24, 26] by integrating the speckle reflections and assembling a direct sum of two components, each of which carries valuable information and could be characterized by a limited amount of parameters. In accordance with this model, we developed a decomposition-based processing scheme for raw ultrasound signals that exploits the inherent redundancy of the data, and achieves an improved compression ratio while preserving the image information.

The proposed decomposition-based compression is equivalent to sparse coding over a two-dictionary set (union of subspaces), that is a mixture of a fixed dictionary for the strong reflectors, based on apriori knowledge of the pulse shape, and a data-driven dictionary for the background component.

The novelty of this model lies in the component-based approach, especially as it concerns the raw signals rather than the beamformed ones or the resulting image. It is clearly desirable to compress the data as early in the processing chain as possible. As far as digital compression is concerned, our approach operates on raw signals "close to the source", i.e. immediately after sampling. Though not yet attempted in the scope of our work, we believe that utilizing the proposed two-component model and learned dictionary, a low rate sampling scheme can be established, such that our algorithm may be extended to the compressed sensing framework. Doing so, our results could be compared with other ultrasound compression techniques currently employed in the analog domain. Furthermore, the potential gain of the component-based approach goes beyond compression. Our experiments indicate that by appropriate alterations to the proposed processing scheme, the resulting image quality may be enhanced, for example by suppressing side-lobe artifacts. Further elaboration on this matter is beyond the scope of this paper.

Finally, we note that the component-based modeling may open more possibilities for analyzing ultrasonic signals. While we identified two main components, other decomposition ideas may be investigated, such as separating the first- and second- harmonic echoes, or detecting more than two components related to various artifacts which require special processing.

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