Conversion of ultrasound IQ data to B-mode images

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***Abstract*— A method is proposed to convert raw IQ data from an ultrasound machine to a scan-converted B-mode image. A variety of noise reduction techniques were applied to the B-mode image and visually inspected afterwards. Based on parasternal short-axis echocardiograms and according to expert observers, qualitatively, the best results were achieved with a dynamic range of 30 – 95dB, user-specified time gain compensation from the ultrasound machine and denoising using hard thresholding on a two level Daubechies-1 wavelet transform.**

Keywords—ultrasound, IQ data, B-mode, conversion, noise reduction

I. Introduction

Ultrasound images are created from sound waves at frequencies above the range audible to humans, typically on the order of 1-10MHz or above [1]. A transducer emits the high frequency waves and records the reflected waves, bounced back from interfaces in the tissue, as a series of time-domain signals [2].

The transducer measures the amplitude and delay of the transmitted sound waves and utilizes this information to create an image of the object [1]. Traditionally, the image is a brightness image, also known as a B-mode image, which is a grayscale, intensity-based representation of the object. The raw signals that the transducer receives are in the radiofrequency range and are known as the radiofrequency (RF) data. A series of signal processing steps are required to convert from the RF data to a B-mode image [3]. One preprocessing step is to demodulate the RF data to baseband and decimate the signal to reduce the bandwidth required to store the data. This new signal is referred to as in-phase and quadrature phase (IQ) signal and is typically represented with complex numbers [3]. In this paper, the term IQ and RF data may be used interchangeably since they both represent the raw data from the transducer but in different formats. Note that there is a difference converting from one format to the other, but both contain all the relevant information in the signals.

Ultrasound is an inexpensive modality compared to MRI or CT, but has a much lower signal-to-noise (SNR) ratio [4]. As a result, it can be difficult to resolve landmarks based on the B-mode image. One way to improve the ability to automatically identify anatomical objects is to utilize the frequency content in the RF data. To facilitate the process, a one-to-one mapping between the RF data and the B-mode image is required. Regions-of-interest (ROIs) can be selected in the B-mode image and the corresponding RF data from that region can be extracted and analyzed. To identify the mapping and create B-mode images suitable for ROI selection, the RF data is used to create a B-mode image. This is one potential use for the proposed method.

Kirkhorn provides an overview of the process of converting between RF data to IQ data [3]. Mari and Cachard briefly discuss the conversion from RF data to B-mode images using an ultrasound machine [2]. Their methods do not employ any speckle reduction techniques to reduce the noise contained in the image. In addition, the Insight Toolkit (ITK), a popular medical imaging library, has an extension library for conversion of RF data to B-mode images but lacks speckle reduction techniques as well [5]. Other work has focused specifically on speckle reduction in ultrasound images but contain no information regarding the RF to B-mode conversion processes [6], [7]. In this paper, a method is developed to convert IQ data from the ultrasound machine to a scan-converted B-mode image. Noise reduction techniques on the resulting B-mode image will also be investigated.

II. Materials and Methods

The raw RF data was acquired using a Mindray Zonare ZS3 ultrasound system using a P4-1c phased array transducer for echocardiographic imaging. Echocardiograms were taken from volunteer females, aged 18-40 with a BMI of 30 to 39.99 kg/m^2 (Obese Class I and II). The following ultrasound images were retrieved from each subject: a parasternal long-axis (PLAX) view, a parasternal short-axis (PSAX) image at the mitral valve level, a PSAX image at the level of the papillary muscles, and a PSAX image close to the apex. The transducer frequency was set to 3.5MHz using tissue harmonic imaging (THI) for increased resolution.

The software in this study was developed and implemented in Python 3.5.4. Additional libraries, including SciPy [8], NumPy [8], scikit-image [9], matplotlib [10], OpenCV [11], and PyQt5 were used in the development. The raw data is saved in a proprietary file format from Zonare. Preliminary MATLAB code was provided to retrieve the data. The first step was to build the same functionality in Python. The ultrasound machine stores the raw data as IQ data, likely due to the reduced bandwidth required to store the data.

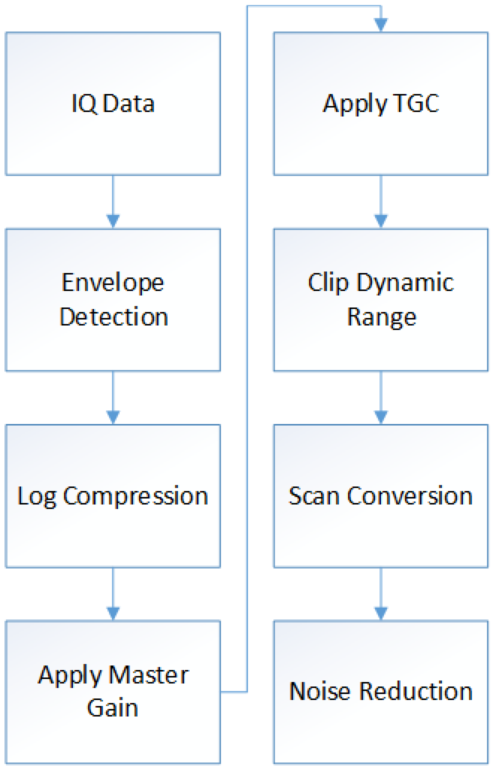

Fig. 1. Block diagram of process for conversion from IQ data to B-mode images.

Fig. 1 above shows the process used to convert from IQ data to B-mode images. With THI, the primary difference from a traditional ultrasound algorithm is the additional block to filter the desired harmonic from the raw data, but this is not necessary because Zonare performs this step before saving the IQ data.

Envelope detection on the raw data is the first step in the algorithm. This is done by taking the magnitude of the complex-valued IQ data using the equation shown in (1). The resulting signal will be real-valued and positive.

$$\sqrt{Re\{IQ\}^2 + Im\{IQ\}^2} \tag{1}$$

Log compression is performed on the magnitude to reduce the dynamic range (DR) of the data to adapt it to the range of a monitor. The magnitude of the data contains large variations in the amplitude such that if it were linearly mapped as an image on a monitor, much of the signal information would be lost because the large amplitude values would overshadow the lower intensity values and they would all map to 0. A nonlinear mapping function can be applied to reduce the large variation in amplitude and preserve signal information. In this case, the nonlinear function used is the log base-10 and the exact equation can be seen in (2). The addition of one to the operand of the log function is to prevent instances of the log of zero, which is negative infinity.

$$20 \log_{10}(1 + x) \tag{2}$$

A master gain is applied to the resulting signal to adjust the overall brightness of the image. The metadata of the Zonare file format has the master gain specified in decibels from -25 to 25dB. Because of the log compression function used, the units of the signal are now in dB and the master gain can be added to each value in the signal due to the multiplicative logarithm property.

Along similar lines, time gain compensation (TGC) applies gain to the resulting signal with the gain varying based on the radial depth. The power of the ultrasound waves decreases proportionally to the square of the distance, thus TGC is applied to provide an even brightness throughout the image. From the Zonare machine, eight TGC knobs, specified in decibels from -20 to 20dB, are linearly interpolated along the A-line and added to the signal.

The image is clipped and normalized with lower and upper bounds to further reduce the DR. At this point in the process, the image contains values between 0 – 70dB. The image will look bright because much of the signal content is in the 50 – 60dB range. By specifying a lower and upper bound, this shifts the histogram of the image to provide the optimal image for viewing.

On account of a phased-array transducer being used in this study, scan conversion must be performed to display a physically accurate B-mode image. A custom library was developed in Python for this purpose titled polarTransform. The following parameters produced the closest shape of the B-mode image compared to the ultrasound machine: initial radius of 30px, final radius of 508px, start angle of 228° and final angle of 308°.

Speckle reduction is the final step of the process. This is an additional step that many of the algorithms described above tend to skip but can be useful in providing a clearer image. A variety of speckle reduction techniques were analyzed experimentally. Perona-Malik anisotropic diffusion is one technique to remove speckle noise and has the additional benefit of preserving edge quality [12]. Wavelet denoising is another method that is frequently mentioned in literature [13]. The Wavelet transform uses basis functions, typically called families, that are scaled and shifted across time to present information about frequencies in the signal but also at what time instance the frequency content is contained. For denoising, a threshold is applied to the transformed image where any values below a particular value are set to zero to remove the content.

There are more classical image processing techniques such as a Gaussian or median filter that can be experimented with as well. A more advanced algorithm, originally designed for removing speckle noise in radar applications, is called the Lee filter and is similar to a Gaussian filter but it does not apply the kernel to edges [14].

For one PSAX echocardiographic scan near the apex, B-mode movies were created varying the dynamic range and speckle reduction technique. Additionally, each speckle reduction technique typically has an adjustable parameter that was varied also. The B-mode images were manually reviewed by experts to qualitatively identify the best parameters in the algorithm. Refer to Fig. 2 for example images throughout the algorithm.

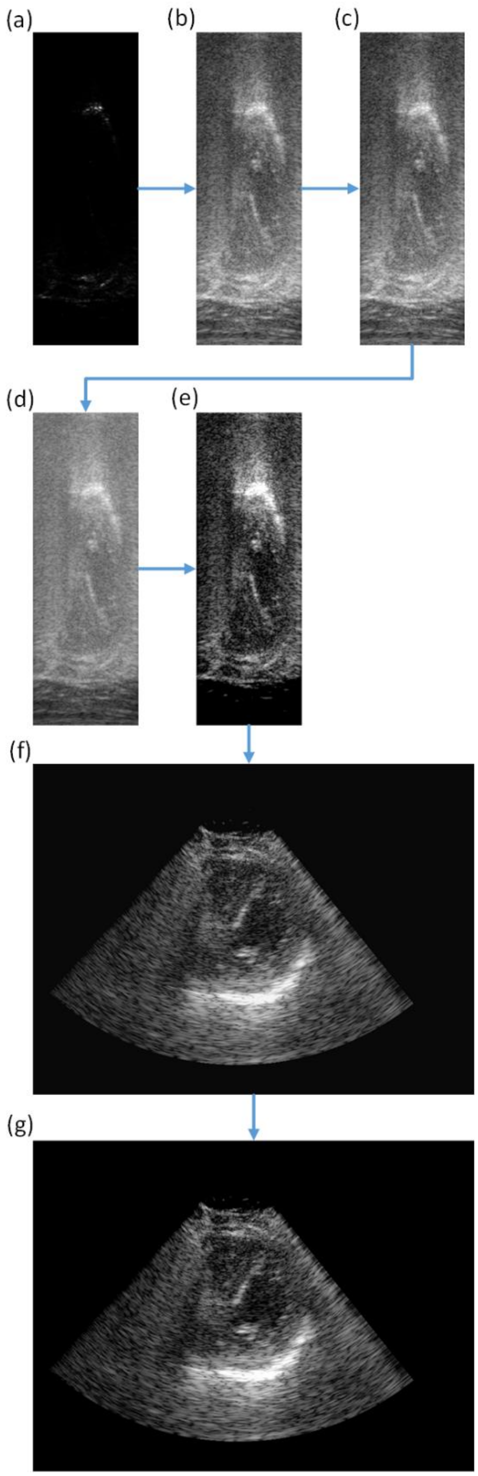

Fig. 2. Example images demonstrating conversion from IQ to B-mode images. Envelope detection in (a) followed by log compression in (b). Master gain is applied in (c) and TGC (d) follows. The DR is clipped in (e). Polar conversion is performed in (f) and finally noise reduction completed in (g).

III. Results

More than fifty B-mode movies were generated as a result of the number of parameters that were varied in this study to be analyzed. These B-mode movies were all generated from one echocardiogram near the apex from the same subject. For the sake of brevity, the best parameters from the noise reduction techniques, as determined by expert observers, were selected and a single frame from each of the B-mode movies were then extracted to demonstrate the quality of the technique. The differences between some noise reduction algorithms are subtle and not easily distinguished by a 2D image but rather are more noticeable when a B-mode movie is played. It is important to note that in this paper the images may look identical, but the addition of a temporal dimension reveals the differences between noise reduction techniques.

The dynamic range was varied from a lower bound of 20 – 55dB and the upper bound from 55 – 125dB. Based on visual inspection, a dynamic range of 30 – 95dB yielded the best resulting image. Fig. 3-7 show examples of B-mode images constructed using the proposed method and the previously described noise reduction techniques. Based on visual inspection once again, the following parameters were chosen for each of the noise reduction techniques as the optimal parameters that produce the best-looking B-mode image:

- Perona-Malik anisotropic diffusion
  - Number of iterations to 5, conduction coefficient (κ) of 30 and speed of diffusion (γ) equal to 0.2
- Gaussian Filter
  - Standard deviation (σ) of 1.5.
- Median Filter
  - Kernel size of 3.
- Lee Filter
  - Kernel size of 3.
- Wavelet's Thresholding
  - Hard thresholding on a two level Daubechies-1 wavelet transform.

In Fig. 8, an example B-mode image from the Zonare ultrasound machine is shown as reference. This image was taken from the same subject and at the same anatomical location as the generated B-mode images in this study.

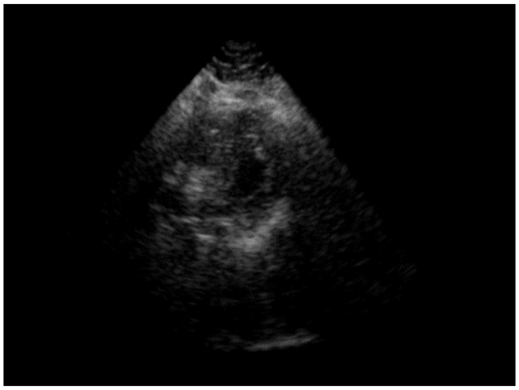

Fig. 3. B-mode image from IQ to B-mode conversion algorithm. Noise reduction technique used was Perona-Malik anisotropic diffusion with number of iterations to 5, conduction coefficient of 30 and speed of diffusion equal to 0.2.

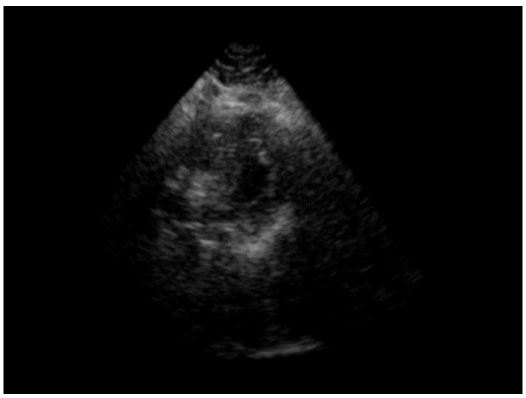

Fig. 4. B-mode image from IQ to B-mode conversion algorithm. Noise reduction technique used was Gaussian filter with standard deviation of 1.5.

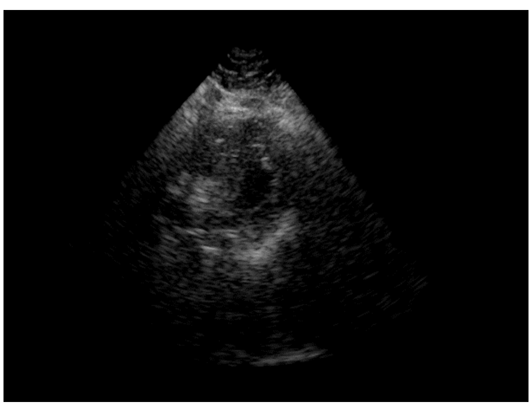

Fig. 5. B-mode image from IQ to B-mode conversion algorithm. Noise reduction technique used was a median filter with a kernel size of 3.

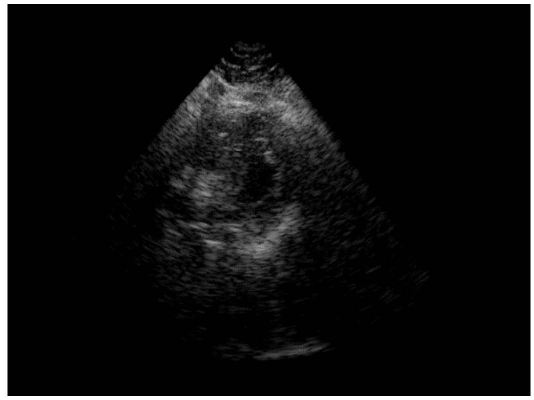

Fig. 6. B-mode image from IQ to B-mode conversion algorithm. Noise reduction technique used was a Lee filter with a kernel size of 3.

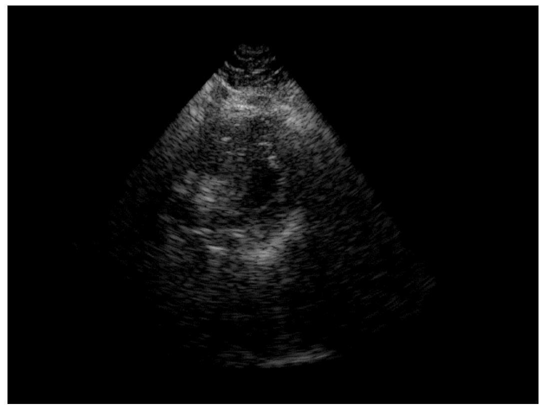

Fig. 7. B-mode image from IQ to B-mode conversion algorithm. Noise reduction technique used was hard thresholding on a two level Daubechies-1 wavelet transform.

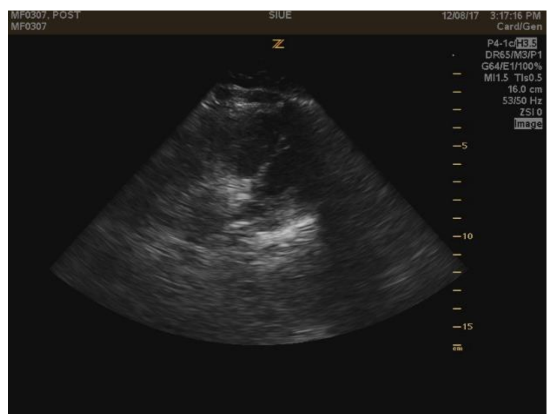

Fig. 8. B-mode image from Zonare ultrasound machine for comparison between proposed method.

IV. Discussion

Key differences between the noise reduction technique are difficult to distinguish from B-mode images but are rather apparent in the B-mode movies. The Gaussian filter performs a per-pixel average based on a neighborhood resulting in the image looking blurry. This is typical of Gaussian filters and is a drawback to using this noise reduction technique although the speckle noise is greatly reduced. A similar blurring effect can be seen using anisotropic diffusion as well. Experts agreed that anisotropic diffusion and Gaussian filters significantly blurred the images to the point of degrading signal quality. However, these two methods are ideal for computer-guided segmentation algorithms where the presence of noise is typically mitigated by greatly smoothing the image.

The median filter, Lee filter and wavelet's transform denoising reduce the speckle less than a Gaussian filter and anisotropic diffusion but result in less blurry images. These three methods are good options for cardiologists because they result in clearer images. The human visual system can very obviously notice when an image is blurry and can handle filtering out speckle noise in their brain fairly well. The differences between these three methods are extremely subtle even for B-mode movies where motion is shown. The three methods seem to perform similarly in terms of filtering speckle noise while preserving edge information. However, according to experts, the best B-mode image was the wavelet's denoising followed by the Lee filter.

Another important measure is whether the B-mode image generated has a SNR comparable to the proprietary B-mode conversion algorithm on the ultrasound machine. For the three recommended methods, median filter, Lee filter and wavelet transform denoising, when compared to the Zonare ultrasound machine B-mode image, tend to show similar information in the images. It is obvious that the dynamic range is smaller in the proposed method due to the overall image looking darker compared to the ultrasound machine's B-mode image. As a result, the edges are further enhanced in the proposed method and are clearer to see. Experts agreed that the B-mode image generated by the proposed algorithm looked better than the B-mode image generated by the ultrasound machine. When asked to describe why the image looks better, the common answer was that the edges look clearer in the proposed method and the B-mode images look like the typical ultrasound images they are accustomed to seeing.

V. CONCLUSION

In this study, an algorithm to convert raw RF data from an ultrasound transducer to a B-mode image is examined. One benefit of using this algorithm rather than the proprietary B-mode conversion algorithms built into many ultrasound machines is that many of the parameters can be tuned after the subject has been scanned. These parameters include dynamic range, time gain compensation and even the speckle reduction algorithm. Many times, the sonographer only has one appointment setup with the subject and must get the parameters setup correctly the first time. In terms of research, this is not ideal because the optimal parameters are not known up front.

Five noise reduction techniques and their corresponding parameters were experimentally analyzed on a given echocardiogram. According to experts, the best-looking B-mode image was created using a dynamic range of 30 – 95dB using wavelet's denoising. Specifically, hard thresholding was applied on a two level Daubechies-1 wavelet transform to reduce the speckle noise in the echocardiogram. In addition, the Lee filter and median filter produced similar results to the wavelet's transform.

When compared to the B-mode image generated by the ultrasound machine, the B-mode image generated in this study fared better according to experts. The key differences were that the B-mode image generated by the proposed method had clearer edges and that the B-mode image resembled other B-mode images that experts were accustomed to seeing.

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