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Evaluating the robustness of dual apodization with cross-correlation

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Abstract

We have recently presented a new method to suppress side lobes and clutter in ultrasound imaging called dual apodization with cross-correlation or DAX. However, due to the random nature of speckle, artifactual black spots may arise with DAX-processed images. In this paper, we present one possible solution, called dynamic DAX, to reduce these black spots. We also evaluate the robustness of dynamic DAX in the presence of phase aberration and noise. Simulation results using a 5 MHz 128 element linear array are presented using dynamic DAX with aberrator strengths ranging from 25 ns RMS to 45 ns RMS with correlation lengths of 3 mm and 5 mm. When simulating a 3 mm diameter anechoic cyst, at least 100 % improvement in the contrast-to-noise ratio (CNR) compared to standard beamforming is seen using dynamic DAX except in the most severe case. Layers of pig skin, fat and muscle were used as experimental aberrators. Simulation and experimental results are also presented using dynamic DAX in the presence of noise. With a system signal-to-noise ratio (SNR) of at least 15 dB, we have a CNR improvement of over 100 % compared to standard beamforming. This work shows that dynamic DAX is able to reliably improve contrast-to-noise ratio in the presence of phase aberration and noise.

I. INTRODUCTION

Ultrasound systems assume a nominal tissue sound speed of 1540 m/s for beamforming. However, different sound speeds in different tissues result in poor focusing of the beam since echoes do not arrive at the focus simultaneously. These effects, generally known as phase aberration, result in lower amplitude of the main lobe, a broadening of the main lobe, and increased clutter levels. There are two main models for aberrations which differ in the aberrator location. The near-field aberration model assumes that the aberrations that contribute most to image degradation occur right at the transducer surface. The aberrations are modeled entirely by changes in the arrival time of the signals at the face of the transducer. However, a more realistic model would incorporate the variations throughout the tissue. This distributed aberration model assumes the aberration varies in range through the imaging plane and is distributed throughout the medium. Many phase aberration correction algorithms are based on a near-field screen model [1]–[7]. Arrival times for each of the elements are calculated based on the geometric relationship between the array elements and the receive focus. The arrival time errors are computed for each element and used to generate an aberration profile. This profile can be used to correct the aberration by adding compensating delays. Methods to improve image quality in the presence of phase aberration in medical ultrasound images of diffuse targets include cross-correlation of neighboring element data [1], [2], maximization of mean speckle brightness [3], [4], and direct estimation using a k-space approach [5]–[7]. After several iterations, these methods seek to converge to a resulting image that is equivalent to an image without phase aberration.

In the nearest-neighbor cross-correlation method (NNCC) [1], [2], phase aberration correction is based on cross-correlation measurements between neighboring elements to estimate the relative time shifts. These time shifts are integrated across the array to calculate improved focusing delays. Since the original transmit focus is degraded by an uncompensated aberration, the procedure requires iteration. In [3] and [4], the element delays are adjusted based on speckle brightness. Since a widening of the imaging point spread function caused by aberration decreases the average speckle brightness in the image [3], this method aims to improve image quality by sequentially adjusting the delay at each array element for maximum speckle brightness. Another approach to delay estimation uses the strong correlation between common midpoint signals when single array elements are used for transmitting and receiving. In their published algorithms, both Rachlin [5] and Li [6] perform cross-correlations of common-midpoint signals. This method uses the fact that transmitter and receiver elements spaced about the common midpoint of the array have similar spatial frequency responses, and a redundant estimate of the time delay at each element can be computed.

Focusing imperfections reduce the coherence of the received signal and decrease the CNR by raising side lobes and clutter. Another group of adaptive imaging methods do not attempt to estimate and correct for the focusing errors but instead minimize the effects of phase aberration, namely the higher sidelobes. These groups include the coherence factor (CF) [8], generalized coherence factor (GCF) [9], [10] spatially variant apodization (SVA) [11], parallel adaptive receive compensation algorithm (PARCA) [12], and a modified version of PARCA, PARCA2 [13]. The coherence factor is defined in the literature [8] as:

$$CF = \frac{\left| \sum_{i=0}^{N-1} S(i) \right|^2}{N \sum_{i=0}^{N-1} |S(i)|^2} \quad (1)$$

where $S(i)$ is the received signal at channel i and N is the total number of channels. A CF value of 1 indicates perfect coherence, and a value of 0 means incoherence. Li expanded the idea of coherence factor to develop the generalized coherence factor (GCF) [9]. The GCF is calculated by first performing the Fourier Transform on channel data after receive delays have been applied. The GCF assumes that the low frequency components of the element domain spectrum correspond to the coherent portion of the received data, and the high frequency components correspond to the incoherent portion. The coherence factor matrix is calculated as the ratio of the spectral energy within a low frequency region to the total energy and is used as a pixel-by-pixel weighting of the image. In synthetic aperture radar (SAR), Stankwitz proposed a spatially variant nonlinear apodization technique, which uses the lateral phase differences between data from Hanning and uniform apodizations. This is accomplished by taking advantage of the properties of raised-cosine weighting functions to find the optimal apodization function on a pixel-by-pixel basis [11]. Another well known adaptive imaging method is parallel adaptive receive compensation algorithm [12]. Using total least squares (TLS), this method works well with a point target, but the improvement is uncertain with speckle targets. A modified version, PARCA2, was also proposed where the parallel beam formation is approximated by a Fourier transform of the aperture data and an iterative scheme is used to simplify the calculation in PARCA [13]. Since DAX is adaptive or target-dependent, it can be considered to fall under this latter group.

In a previous work [14], we presented a new method called dual apodization with cross-correlation, or DAX, to suppress side lobes and clutter in ultrasound imaging. The premise of

our earlier work was that we can create two point spread functions (PSFs) having similar main lobes and different clutter signals with two different receive apodization or aperture functions. Using axial normalized cross-correlation of RF signals, we can distinguish main lobe dominated signals from clutter dominated signals. For each pixel, axial segments of RF data, roughly two to four wavelengths long, from the two apodized and beamformed RF data sets are cross-correlated. Main lobe signals from the two RF data sets have a cross-correlation value higher than 0.96 while clutter-dominated signals have a much lower cross-correlation. With the alternating pattern, the RF data from RX1 and RX2 in the grating lobe region are essentially 180° out of phase with respect to each other giving a normalized cross-correlation coefficient near -1 . This fact allows us to distinguish main lobe dominated signals from clutter dominated signals. In the proposed method, if the coefficient is greater than or equal to a set threshold value $\epsilon > 0$, then the sample value is multiplied by the cross-correlation coefficient. If the coefficient is less than the threshold value ϵ , this signal is considered to be mainly clutter. It is suppressed by multiplying the sample value by the threshold value ϵ . In our case, ϵ was set to 0.001 which is a 60 dB reduction in magnitude. This threshold of 0.001 is chosen instead of zero since multiplying a sample by zero would yield errors when taking the logarithm of the detected data. Signals having a comparable mixture of main lobe and clutter will receive a reduction between 0 and 60 dB depending on the value of the cross-correlation coefficient.

Four pairs of apodization functions are presented: a uniform-Hanning apodization, two apertures with a common midpoint, two randomly selected apertures and two alternating patterns. The randomly selected apertures and alternating patterns both use mutually exclusive elements. While all apodization schemes showed improvement in CNR, the alternating pattern had the highest CNR experimentally followed by the randomly selected aperture pattern. The uniform-Hanning and common midpoint schemes showed significant improvement in simulations but less improvement at lower sampling rates, which is the case for many clinical ultrasound systems.

In this paper, we describe results from computer simulations and phantom experiments to evaluate DAX performance in the presence of phase aberration and noise. Simulation and experimental results using a 5 MHz 128 element linear array show that DAX is able to lower sidelobe levels and significantly reduce clutter levels in the presence of phase aberration. Experimentally, a subcutaneous pig fat layer was interposed between the ultrasound transducer and phantom to emulate the effects of phase aberration. CNRs are calculated to quantify improvements and identify the limitations of DAX. To examine the effects of electronic noise, simulation and experimental results are presented with 35 dB, 25 dB and 15 dB system SNRs.

II. METHODS

In all simulations and experiments, we used an alternating pattern of enabled elements in receive mode to create the two apodization functions which, in combination, were shown to have the highest CNR experimentally [14]. A detailed system block diagram of the alternating pattern is shown in Fig. 1. For transmit, a uniformly weighted subaperture of 64 elements was used to focus at a single depth of 30 mm. On receive, the signals from transducer elements in the darker gray shading were delayed and summed to create RX1. The signals from elements with a lighter shading were delayed and summed to create RX2. If clusters of 8 elements are used, we call this pattern the 8-on, 8-off pattern, or 8-8 alternating pattern. Different versions such as 6-6, 4-4, or 2-2 could be used under various conditions. The criteria to decide which version to use will be discussed later in this paper. Axial segments of RF data, roughly two to four wavelengths long, from the two beamformed RF data sets are cross-correlated to determine the amount of mainlobe dominated signal and to create a weighting matrix. Due to the random nature of speckle, artifacts in the form of black spots may arise with DAX-processed images. To minimize these occurrences, the weighting matrix was median filtered with a window size

of $2\lambda \times 2\lambda = 0.6 \times 0.6$ mm, where λ is the wavelength. Median filtering is a simple way to suppress impulse noise [15]. This window size was chosen to be large enough to remove the effect of most artifacts but small enough to minimize blurring of the weighting matrix. The standard delay-and-sum beamformed data with uniform apodization, labeled as “Standard beamformed data” in Figure 1, are given by the sum of RX1 and RX2. After bandpass filtering, the standard beamformed data is multiplied by the thresholded and filtered cross-correlation coefficients to yield a DAX RF dataset. This data set will go through additional standard signal processing steps such as bandpass filtering, envelope detection, and log compression. Given a 1λ pitch between elements, the alternating receive apertures RX1 and RX2 will yield grating lobes. However, the RF data from RX1 and RX2 in the grating lobe region are essentially 180° out of phase giving normalized cross-correlation coefficients near -1 .

To begin our evaluation, simulations with a point target and a cyst with varying aberration and noise strengths were performed using Field II [16]. A 5 MHz Gaussian envelope pulse with 50 % bandwidth was used as a transmit pulse, and a delta function was used as the element impulse response. For a point target simulation, an RMS energy value was calculated from the received voltage trace. All RMS energy values were converted to decibels after normalizing to the maximum energy level. The focus for both transmit and receive was fixed at a 30 mm depth for the point target simulations. Since point targets are rarely found in the clinical environment and DAX is a target-dependent technique, we have also performed simulations using cylindrical 2, 3, and 4 mm diameter anechoic cysts located at depths of 20, 30 and 40 mm respectively embedded in a 3-D phantom of scatterers. Based on a previously published analysis [17], we used 10 scatterers per resolution cell to create a $10 \text{ mm} \times 40 \text{ mm} \times 50 \text{ mm}$ (elevation $\times$ lateral $\times$ axial) phantom filled with speckle generating scatterers. The following array imaging parameters in Table 1 were used. These imaging parameters were chosen to model the Ultrasonix Sonix RP ultrasound system (Ultrasonix Medical Corporation, Richmond, BC, Canada) and L14-5/38 linear array used in the experimental component of this paper.

Aberration parameters ranging from 25–45 ns root-mean-square (RMS) and 3 mm and 5 mm correlation lengths were used. To test the performance of DAX in the presence of aberration, 100 realizations of each aberrator were used for a point target simulation. Because of limited computing resources and a large number of scatterers present in the 3-D phantom, we performed five realizations of each aberrator for a cyst target simulation. Fig 2. shows examples of the three aberration profiles. These aberrators are created by convolving Gaussian distributed random numbers with a Gaussian function which is applied to both transmit and receive [18]. For all cysts targets, performance was evaluated using the CNR in equation (2) [2]:

$$CNR = \frac{\overline{S_t} - \overline{S_b}}{\sigma_b} \quad (2)$$

where $\overline{S_t}$ is the mean of the target, $\overline{S_b}$ is the mean of the background and σ_b is the standard deviation of the background of the envelope-detected, log-compressed image. To test the performance of DAX in the presence of noise, 100 realizations of random zero-mean Gaussian noise were added to achieve a system SNR of 35, 25, and 15 dB. Integrated beamplots and cyst images with SNRs of 35, 25, and 15 dB were created and evaluated quantitatively in terms of beamwidths, clutter level and CNR.

For our experimental setup, individual element RF signals were collected for offline processing from an ATS spherical lesion phantom (ATS laboratories, Bridgeport, CT, Model 549) containing 2, 3, and 4 mm anechoic cysts using an Ultrasonix Sonix RP ultrasound system having a 40 MHz sampling frequency. This system has great flexibility allowing the researcher

to control parameters such as transmit aperture size, transmit frequency, receive aperture, filtering, and time-gain compensation. In this experiment, a 128-element, 300 μm pitch, L14-5/38 linear array was used. A 1-cycle transmit pulse with a center frequency of 5 MHz, and a subaperture size of 64 elements, or 19 mm, was used. On receive, element data was collected, and receive beamforming was done offline with a constant f-number = 1.5 using Matlab (The MathWorks, Inc. Natick, MA). Dynamic receive focusing was used with focal updates every 100 μm in range and an image line spacing of 75 μm . Data from each channel was collected 32 times and averaged to minimize the effects of electronic noise in all experiments. To mimic a near field aberration of the body wall consisting of skin, fat, and muscle encountered in clinical ultrasound imaging, 3 mm–11 mm thick layers of pork belly were used (99 Ranch Market, San Gabriel, CA). To mimic a weak aberrator, only a 3 mm thickness of skin from the pork belly was used. Next, a 4 mm thickness of fat and muscle aberrator was used. Lastly, a 11 mm thickness of fat and muscle was used. To simulate different levels of noise, we added Gaussian white noise to achieve system SNRs of 35, 25, and 15 dB.

III. SIMULATION RESULTS

A. Point target simulation in the presence of noise

Fig. 3 shows one of the 100 realizations with system SNRs of 35, 25, and 15 dB before and after applying the DAX 8-8 alternating algorithm. The noise level was determined with respect to the peak value of RF data. From these results, we see that DAX is able to suppress noise by a factor of 30 dB assuming that the noise on each channel is uncorrelated. The mean reduction in the clutter level was from -36 dB to -67 dB, from -26 dB to -56 dB and from -16 dB to -46 dB with system SNR of 35 dB, 25 dB and 15 dB respectively. The noise suppression capability of the DAX algorithm can be explained as follows. The cross-correlation of two sets of uncorrelated noise will have an expectation value of zero. However, after thresholding of the cross-correlation coefficients, the new expectation value will be greater than zero. We have empirically quantified the new expectation value by performing 2000 realizations of the cross-correlation and thresholding. The mean reduction was 0.0316 or -30 dB.

B. Cyst simulation in the presence of noise

Cyst simulations were also performed in the presence of the same noise levels. Fig. 4 shows the simulation results with 3 mm diameter cyst with 35 dB, 25 dB and 15 dB system SNRs before and after applying the DAX 8-8 alternating algorithm. The logarithmically compressed images are displayed with 50 dB dynamic range. Regions used to calculate CNR are shown in the white and black rectangles for the target and background respectively. With a 35 dB SNR, clutter inside the cyst with standard beamforming is increased which results in a lower CNR value (Fig. 5). With a 25 dB SNR, clutter inside the cyst with standard beamforming is further increased which results in lower CNR value. When the SNR is further decreased to 15 dB, it is harder to see the cyst in the standard image due to raised clutter inside the cyst. DAX is able to improve CNR by over 100 % in all cases and restore visibility of the cyst. From these results, we can see that the DAX algorithm is able to suppress noise-dominated signals at SNRs of 15 dB or greater. The CNR values are shown in Fig. 5. The error bars span ± 1 standard deviations from the mean CNR.

C. Point target simulation in the presence of phase aberration

Fig. 6 shows a representative instance from 100 simulated beamplots using standard beamforming with uniform receive apodization and with the DAX 8-8 alternating pattern in the presence of no aberration and aberrators with 25 ns RMS, 5 mm correlation length, 35 ns RMS, 5 mm correlation length, and 45 ns RMS, 3 mm correlation length. In the case of no aberration, DAX removes most of the clutter below -40 dB. With the 25 ns RMS, 5 mm correlation length aberrator, DAX is able to remove most of the clutter below -30 dB. Since

this is considered to be a fairly weak aberrator, similar performance to the case of no aberration is seen. With the 35 ns RMS, 5 mm correlation length aberrator, higher side lobes and clutter levels are seen. DAX is effective in lowering clutter levels away from the main lobe by more than 40 dB. Lastly, with the 45 ns RMS, 3 mm correlation length aberrator which is a severe aberration, high sidelobes are seen. Most of the clutter away from the main lobe has been removed using DAX. Fig. 7 shows the mean -6 , -20 , -40 , and -60 dB beamwidths for all three aberrators from 100 realizations. The error bars span ± 1 standard deviations from the mean beamwidth. In all cases, DAX is able to decrease the beamwidths and clutter.

D. Single cyst simulation with Dynamic DAX

Due to the random nature of speckle, artifacts may arise with DAX-processed images. Simulated images of a 3 mm cyst at a 30 mm depth were obtained using Field II. Fig. 8 shows images of the cyst with a 30×10 mm field of view for various DAX alternating patterns, 2-2, 4-4, and 8-8 (Fig. 8. a–c). The regions used to calculate CNR are shown in the white and black rectangles for the target and background respectively. The CNR improves using larger alternating patterns as listed in Table 2, but artificial black spots are more visible with larger alternating patterns. Black spots are more prevalent in the 8-8 image but are not present near the transmit focus of 30 mm in all cases. These black spots could be minimized by using multiple transmit foci, but this strategy would reduce frame rate. As an alternative, we propose using a modified version of DAX called dynamic DAX if only one transmit focus is used. Similar to dynamic focusing, dynamic DAX uses a different alternating pattern at different depths depending on the distance away from the transmit focus. For example, by observing the range where artifacts appear, DAX would not be used at depths less than 19 mm if the transmit focus is located at 30 mm. A 2-2 alternating pattern would be used for depths between 19–25 mm, 4-4 would be used for depths 25–29 mm, 8-8 would be used for 29–33 mm. 4-4 would then again be used from 33–42 mm, and 2-2 is used from 42–60 mm. The result is essentially a composite image from Figs. 8. (a)–(c) and is shown in Fig. 8. (d).

The sequences used for dynamic DAX lead us to hypothesize that these black spots arise when the grating lobe signal is the dominant portion of the signal since grating lobe and clutter levels rise at depths away from the transmit focus. To test this hypothesis, we performed Field II simulations to examine the magnitude of grating lobes of the beam at each depth. Depths ranging from 15–50 mm at 1 mm increments were used. DAX with alternating patterns of 2-2, 4-4, and 8-8 were done. Fig. 9 shows the grating lobe beam magnitude versus depth for each alternating pattern. The receive focus was set to the specific depth of interest, and the transmit focus was always set to 30 mm. As expected, the grating lobe magnitude increases with distance away from the transmit focus located at 30 mm and also with an increasing alternating pattern. The magnitude of the grating lobe is not symmetrical around the focus but decreases with depth. This implies that we could use a wider range of larger alternating patterns after the transmit focus. Examining where the peak of the grating lobes become greater than -25 dB in Fig. 9 closely relates to the depth at which black spots in the images appear in Fig. 8. This is not a surprising result since signals with a grating lobe signal that is comparable to a main lobe signal in magnitude would give a wide variation of cross-correlation coefficients. Therefore, the following dynamic DAX sequence has been used for all simulations and experiments when the transmit focus was at 30 mm with an f-number of 1.5:

1. DAX is not used at depths less than 19 mm.
2. A 2-2 alternating pattern is used for depths between 19–25 mm,
3. A 4-4 alternating pattern is used for depths 25–29 mm,
4. An 8-8 alternating pattern is for 29–33 mm.
5. A 4-4 alternating pattern is then again used from 33–42 mm, and

6. A 2-2 alternating pattern is used from 42–60 mm.

The DAX sequence will depend on the transmit focus and the f-number. If we shift the transmit focal depth, then the pattern will be shifted by the same amount. If we reduce or increase the f-number, the depth of field will be decreased or increased by factor of the f-numbersquared. This allows us to use a larger range for the 8-8 pattern in this focal region. Table 3 shows an example of how to determine a particular dynamic DAX sequence.

E. Multiple cyst simulation with Dynamic DAX

To examine the effect of dynamic DAX, a simulation with multiple cysts was used. Three cysts with diameters 2, 3, and 4 mm were placed at a depth of 20, 30, and 40 mm respectively. These cysts were chosen to simulate the ATS tissue mimicking phantom used in the experimental component of this paper. The transmit focus was fixed at a 30 mm depth for the simulation. Dynamic receive focusing was used with focal updates every 100 μm for both standard and dynamic DAX images with an f-number of 1.5. Fig. 10 shows the results of the simulation. The cyst images obtained by using dynamic DAX processing are more visible than the images obtained with standard beamforming. Regions used to calculate CNR are shown in the white and black rectangles for the target and background respectively. The CNR for the 2 mm cysts is 1.84 for the standard beamformed case, and DAX yields a slight improvement to 2.16. Qualitatively, the cyst is only slightly more visible using DAX. For the 3 mm cyst, a CNR of 5.69 for standard beamforming is improved to 13.40 using dynamic DAX. The 4 mm cyst also shows a significant improvement in CNR from 2.90 to 9.40. We could use a larger alternating pattern after the transmit focus, which may explain why there is a larger CNR improvement with the 4 mm cyst located after the transmit focus than with the 2 mm cyst located before the transmit focus. The 4 mm cyst exhibits a large amount of clutter which resulted in a smaller looking less circular cyst, but this is also seen in the standard beamformed case. Using an additional transmit focus here may restore the circular shape of the cyst. The CNR values are listed in Table 4.

F. Multiple Cyst simulation in the presence of phase aberration

To further examine the effect of dynamic DAX in the presence of phase aberration, the same multiple cyst phantom was used with the aberrators shown in Fig. 2. We have performed five realizations of Field II simulations to assess the performance of DAX in the presence of phase aberration. We have also compared the DAX algorithm with GCF [9] in terms of CNR. Fig. 11 show simulated cysts using standard beamforming with uniform receive apodization, GCF with $M_0 = 2$ (using Li's notation) and with dynamic DAX in the presence of aberrators with 25 ns RMS, with 5 mm correlation length, 35 ns RMS, with 5 mm correlation length, and 45 ns RMS, with 3 mm correlation length. The images are displayed over a 50 dB dynamic range. The transmit focus was fixed at a 30 mm depth for the simulation. Dynamic receive focusing was used with focal updates every 100 μm for both standard and dynamic DAX images with an f-number of 1.5.

With a 25 ns, 5mm aberrator, an improvement in CNR from 1.72 ± 0.19 to 2.29 ± 0.17 , from 3.66 ± 0.34 to 9.86 ± 0.80 and from 2.27 ± 0.44 to 10.05 ± 0.62 is seen for the 2 mm, 3 mm and 4 mm cysts respectively. Qualitatively, the 3 mm cyst which is located at the transmit focus appears circular, but not the 2 mm and the 4 mm cysts which are away from the transmit focus. Some clutter at the top right corner of the 4 mm cyst can also be seen. In the case of a 35 ns, 5 mm FWHM aberrator, a CNR improvement from 1.45 ± 0.19 to 1.96 ± 0.30 , from 3.42 ± 0.61 to 10.17 ± 0.71 and from 2.28 ± 0.81 to 7.91 ± 0.91 is seen for the 2 mm, 3 mm and 4 mm cysts respectively. Again, the 3 mm cyst which is located at the transmit focus appears circular but not the cysts which are away from the transmit focus. The 4 mm cyst has clutter at the top left corner. More black spots can also be observed away from the focus. In the case of a 45 ns,

3 mm FWHM aberrator, a CNR improvement from 1.01 ± 0.25 to 1.38 ± 0.37 , from 1.65 ± 0.50 to 2.41 ± 1.62 and from 0.96 ± 0.13 to 4.47 ± 0.95 is seen for the 2 mm, 3 mm and 4 mm cysts respectively. DAX is not able to completely remove clutter inside the cysts. Overall, a more significant improvement in CNR is seen for the 4 mm cyst than the 2 mm cyst. This can possibly be explained by the fact that the 4-4 pattern was used for the 4 mm cyst which gives a higher CNR than the 2-2 pattern which was used for the 2 mm cyst. Also, it is typically easier to detect a larger lesion. The mean CNR values for each aberrating case are shown in Fig. 12. The error bars span ± 1 standard deviations from the mean CNR.

IV. EXPERIMENTAL RESULTS

A. Cysts in the presence of noise

Cyst imaging experiments were also performed in the presence of the different noise levels. First, a system SNR of 40 dB at the transmit focus from the speckle region was measured using the method described in [19]. To test the performance of DAX in the presence of noise, random zero-mean Gaussian noise was added to decrease the system SNR down to 35 dB, 25 dB and 15 dB. Fig. 13 shows the results with 3 mm diameter cyst with 35 dB, 25 dB and 15 dB SNRs, before and after applying the DAX 8-8 alternating algorithm. Regions used to calculate the CNR are shown in the white and black rectangles for the target and background respectively. The images are displayed with a 50 dB dynamic range. With a 35 dB SNR, clutter inside the cyst with standard beamforming is increased which results in lower CNR value (Fig. 14). With DAX, the CNR is increased by 150 %. With a 25 dB SNR, clutter inside the cyst is further increased with standard beamforming. With DAX, the CNR is increased by 130 %. When the noise level is further increased to -15 dB, it is harder to see the cyst in standard image due to raised clutter inside the cyst and variation in the speckle region. DAX is able to improve the CNR by over 140 % and restore the visibility of the cystic region. However, the black artifacts in the speckle region are also increased. From these results, DAX could be used for an SNR greater than 15 dB. The mean CNR values are shown in Fig. 14. The error bars span ± 1 standard deviations from the mean CNR.

B. Cyst experiment with pig skin and fat layer

To test the effects of phase aberration experimentally, a pig skin layer was placed in between the ultrasound transducer and the ATS cylindrical lesion phantom containing 2 mm, 3 mm and 4 mm anechoic cysts to induce phase aberrations and beam distortion, to determine whether DAX reduces the effect of beam distortion and image clutter. We have also compared DAX with the GCF algorithm with $M_0 = 2$ in terms of CNR. At 24°C, the speed of sound of pig fat is 1420–1444 m/s and of pig skin/muscle varies from 1720 m/s to 2000 m/s [20]. The temperature of the test phantoms and the pig fat layer was approximately 22 °C (room temperature, normal testing conditions) during the experiment. Images with no aberration of the ATS phantom are shown in Fig. 15. The CNR improves with dynamic DAX for all three cysts. The improvement is more dramatic for the 3 mm diameter cyst which is located at the transmit focus and where the 8-8 alternating pattern was used (Table 5). For all experimental images, the dynamic DAX images were generated using the same sequence used for simulation, where the 8-8 pattern was used for the transmit focal region. The transmit focus was always set to the depth of the 3 mm diameter cyst.

With a skin layer of 3 mm thickness and a fat/muscle aberrator of 4 mm in thickness, a dramatic improvement in CNR can be observed (Figs. 16–17, Table 5). The transmit focus was set to 33 mm and 34 mm for the 3 mm and 4 mm aberrators respectively to maintain a focus at the 3 mm diameter cyst. Lastly, the thick 11 mm fat/muscle aberrator created the most clutter in the cysts, but dynamic DAX was yet able to improve the CNR (Fig. 18, Table 5). Here, the transmit focus was set to a depth of 41 mm.

V. DISCUSSION AND FUTURE WORK

The dynamic DAX algorithm has been shown to improve contrast in anechoic cysts in the presence of phase aberration and electronic noise. The improvement in CNR was shown through simulation and experiments using a commercial phantom and excised porcine tissue. The DAX algorithm was also compared with GCF with $M_0 = 2$ in the presence of phase aberration in terms of CNR. DAX performed better than GCF in most cases, especially at the transmit focus. DAX is also computationally efficient. Using Windows XP, 3.4 GHz, 3 GB RAM and MATLAB 7 R14, the cross-correlation process with segment length of 41 samples took 26 seconds with the data sets shown in Fig. 15–Fig. 18. Standard beamforming took 39 seconds, and GCF processing took 51 seconds. In the presence of noise or phase aberration, the DAX algorithm was not able to restore the distorted cyst boundary and shape. A modified smoother version of the weighting function, filtering of coefficient matrix, and optimizing correlation kernel and filter lengths might aid to restore cyst boundaries. We are currently investigating these options.

With dynamic DAX, the decision on which alternating pattern to use at various depths should be specified to achieve an optimal result. Around the focal region, a large alternating pattern such as 8-8 shows the biggest improvement in CNR. However, away from the transmit focus, artificial black spots in the background region can be seen due to rising grating lobe magnitudes relative to the main lobe. These artifacts become more prevalent with stronger aberrators. In any clinical setting, removing all artificial black spots is necessary. This can be achieved in several ways: 1) by using dynamic DAX where different alternating apodization functions are used as a function of depth as described in this paper, 2) using multiple transmit foci and using DAX at depths near the transmit foci, or 3) using previously reported data on phase aberration on different parts of the body or estimating aberrator strength through NNCC and using an appropriate dynamic DAX configuration. The first method has been shown to work well in this paper. The second method of using multiple transmit foci would lower the frame rate. However, it will give higher overall CNR throughout the image and might be more robust with stronger aberrators. The third method is probably the most useful in clinical situation, but requires further work to collect data on different patients.

Considerable processing may be needed to decide which alternating pattern should be used at various depths for different patients. This problem may be alleviated by using a smaller alternating pattern such as 2-2 or 4-4 and also taking into account patient history, target organ, depth and other relevant aspects that will have a different aberrating effect. In breast ultrasound for example, women in different age groups may have different correlation lengths and aberrator profiles. Past clinical measurements of breast arrival time errors have varied from about 17 ns RMS to 42 ns RMS with correlation lengths ranging from 3.5 mm to 8 mm [21]. The data suggests that we could possibly model the aberration occurring in the breast with weak (25 ns with 5 mm FWHM) to hard aberrators (45 ns with 3 mm FWHM) as described in this paper. Hopefully, in the future, more complete clinical data will be available on correlation lengths and aberrating time delays in breast depending on age groups, body types, and other clinical information. Then, pre-defined DAX sequences can be used.

Future work will focus on evaluating DAX using *in vivo* data. Another area of work will focus on combining DAX with other phase aberration correction algorithms. Many phase aberration correction algorithms are iterative, and using DAX after one or two iterations may show greater improvement and efficiency than with DAX alone or with the phase aberration correction algorithm alone.

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Fig. 1.
System block diagram for the DAX alternating pattern

Fig. 2. Aberration profiles of 25 ns RMS 5mm FWHM (solid line), 35 ns RMS 5mm FWHM (dashed line) and 45 ns RMS 3mm FWHM (dotted line)

Fig. 3.
Lateral Beamplots with 35 dB, 25 dB and 15 dB SNR using standard beamforming and DAX.
These beamplots show the effects of noise on the point spread function

Fig. 4. 3 mm diameter cyst simulations with (a) 35 dB SNR, (b) 25 dB SNR, and (c) 15 dB SNR

Fig. 5. Mean CNR values of 100 realizations for cyst simulations with different levels of system SNR. The error bars span ± 1 standard deviations from the mean CNR.

Fig. 6.

Lateral beamplots in the presence of (a) no aberration, (b) 5mm FWHM, 25 ns RMS, (b) 5mm FWHM, 35 ns RMS, and (d) 3mm FWHM, 45 ns RMS aberration. Beamplot for RX1 is shown in dashed/dotted line, beamplot for RX2 in dotted line, standard beamforming with uniform apodization in dashed line, and DAX 8-8 alternating pattern in solid line.

Fig. 7.

The mean beamwidth of 100 realizations with (a) 25 ns RMS, 5mm FWHM, (b) 35 ns RMS, 5mm FWHM and (c) 45 ns RMS, 3mm FWHM aberrators using standard beamforming and DAX. The error bars span ± 1 standard deviations from the mean beamwidth.

Fig. 8.
Simulated cyst image using (a-c) different alternating patterns and (d) dynamic DAX

Fig. 9.
Grating lobe magnitude vs receive focus when the transmit focus is set to 30 mm depth

Fig. 10.
Simulated multiple cyst images using standard beamforming with uniform apodization and dynamic DAX

Fig. 11. Simulated multiple cyst images with standard beamforming with uniform apodization, GCF and dynamic DAX in the presence of (a) 25 ns RMS, 5 mm FWHM aberrator, (b) 35 ns RMS, 5 mm FWHM aberrator and (c) 45 ns RMS, 3 mm FWHM aberrator

Fig. 12.

The mean CNR of five realizations with (a) 25 ns RMS, 5mm FWHM, (b) 35 ns RMS, 5mm FWHM and (c) 45 ns RMS, 3mm FWHM aberrators using standard beamforming, GCF and DAX. The error bars span ± 1 standard deviations from the mean CNR.

Fig. 13.

Experimental cyst images with standard beamforming with uniform apodization and DAX 8-8 alternating pattern with (a) 35 dB SNR (b) 25 dB SNR and (c) 15 dB SNR

Fig. 14.

Mean CNR values of 100 realizations for cyst experiments with different levels of system SNR.

The error bars span ± 1 standard deviations from the mean CNR.

Fig. 15.
Experimental cyst images with no aberrator

Fig. 16.
Experimental cyst images in the presence of a skin layer aberration of 3 mm in thickness

Fig. 17.

Experimental cyst images in the presence of a fat/muscle layer aberration of 4 mm in thickness

Fig. 18.

Experimental cyst images in the presence of a thick muscle layer aberration of 11 mm in thickness

Table 1 1×128 Linear Array and Imaging Parameters

Parameter	Value
Number of elements in subaperture	64
Center Frequency	5 MHz
Bandwidth	50 %
Azimuthal Element Pitch	300 μm
Azimuthal Element Width	279.8 μm
Elevation Element Height	5 mm
Sound speed	1540 m/s
Transmit Focus	30 mm
Lateral beam spacing	75 μm
Receive focal delay step (cyst)	100 μm

Table 2

CNR values with different alternating patterns and dynamic DAX

	2-2	4-4	8-8	Dynamic DAX
CNR	8.57	12.02	12.55	12.60

Table 3

Dynamic DAX sequence for different focal depths and f-numbers

f-number 1.5, transmit focus @ 30 mm	f-number 2, transmit focus @ 41 mm	Dynamic DAX sequence
< 19 mm	< 30 mm	No DAX
19–25	30–36	2-2
25–29	36–39	4-4
29–33 (4 mm)	39–46 (7 mm)	8-8
33–42	46–53	4-4
42–50	-	2-2

Table 4

CNR values of three different sized cysts using dynamic DAX

	Standard with uniform apodization			Dynamic DAX		
	2 mm	3 mm	4 mm	2 mm	3 mm	4 mm
CNR	1.84	5.54	2.90	2.16	13.10	9.40

Table 5

Experimental CNR values in the presence of phase aberration

	Uniform Apodization		GCF		Dynamic DAX		
	2 mm	3 mm	4 mm	2 mm	3 mm	4 mm	4 mm
No aberrator	1.72	4.40	4.11	2.18	6.02	5.41	7.95
Skin layer	2.01	3.84	2.89	2.65	5.01	3.90	7.43
Fat/muscle layer	2.24	3.34	3.72	2.52	4.51	4.84	6.74
Thick muscle layer	1.59	2.63	2.05	2.22	3.26	2.98	3.59