MEDICAL ULTRASOUND IMAGING USING THE FULLY ADAPTIVE BEAMFORMER

Magali Sasso and Claude Cohen-Bacrie

Philips Research, 345 Scarborough Road, Briarcliff Manor, NY 10510, USA

ABSTRACT

Medical ultrasound beamforming is conventionally done using a classical delay-and-sum operation. This simplest beamforming suffers from drawbacks. Indeed, in phased array imaging the beamformed radio-frequency signal is often polluted with off-axis energies. In this paper, we investigate the use of an adaptive beamforming approach widely used in array processing, the fully adaptive beamformer, to reduce the bright off-axis energies contribution. We show that the fully adaptive beamformer cannot be applied to medical ultrasound as it was initially derived since medical ultrasonic medium produces coherent or highly correlated signals and the algorithm fails to work within this context. The spatial smoothing preprocessing is introduced which allows the fully adaptive beamformer to operate. A complementary preprocessing that uses the received data obtained using consecutive transmission lines further improve the performances. Very promising results as for the application of adaptive array processing techniques in medical ultrasound are obtained.

1. INTRODUCTION

In medical ultrasound, beamforming is done with the simplest technique that consists of a delay and sum of the per-channel received data. In various fields dealing with array processing such as sonar, radar, telecommunication this process would appears as archaic. Indeed, since the 60's very efficient techniques to do beamforming in an adaptive way have been developed. This reduces the noise and non-desired signals contribution leading to very good results. This paper proposes an adaptation of one of these adaptive array processing techniques to medical ultrasound to enhance beamforming and consequently the image formation.

We consider here the first adaptive beamforming technique devised by Capon in 1969 [1]. This algorithm globally minimizes the array output power coming back from the medium while maintaining a gain of one in the direction of the received beamformed line. The process affects the beampattern by steering nulls in directions of interferers greatly reducing their contribution. Since contexts and hypotheses are widely different in medical ultrasound from other array processing fields, implementation of array processing techniques raises some significant issues. This paper investigates ways to successfully implement the algorithms on received data which suffer from a high degree of correlation.

2. FULLY ADAPTIVE BEAMFORMER (FAB)

Consider an array of M equally spaced transducers and P emitting point sources in the near-field. Complex (analytic signal) notation will be used throughout. Superscript † will be used to denote the complex conjugate transpose. In the presence of diffuse ambient noise, the received signal by the array is:

$$\underline{x}(t) = \mathbf{A}\,\underline{s}(t) + \underline{n}(t) \tag{1}$$

where $\underline{x}$ is the M x 1 received signal vector, $\underline{s}$ is the P x 1 source vector, $\underline{n}$ is the M x 1 received noise vector and $\mathbf{A}$ is the M x P matrix containing the response vectors of the medium between each sensor and each source. Under the assumption that the noise is zero-mean and uncorrelated with the sources, the spatial covariance matrix of the received signal is given by:

$$\mathbf{R_{xx}} = \mathbf{A}\mathbf{R_{ss}}\mathbf{A}^\dagger + \mathbf{R_{nn}} \tag{2}$$

where, $\mathbf{R_{ss}} = \mathbb{E}[\underline{s}.\underline{s}^\dagger]$ is the source auto-covariance matrix and $\mathbf{R_{nn}} = \mathbb{E}[\underline{n}.\underline{n}^\dagger]$ is the noise auto-covariance matrix.

The FAB has been introduced in 1969 by J. Capon [1] and is also referred as Capon beamformer, minimum variance distortionless response or maximum likelihood beamformer. It is a criterion that focuses the beam in direction θ by minimizing the array output power under the constraint of gain unity in direction θ. The optimal weight vector, $\hat{\underline{w}}$, is obtained as a solution to the optimization problem:

$$\hat{\underline{w}} = \arg\min_{\underline{w}} \ \underline{w}^\dagger \mathbf{R_{xx}} \underline{w}$$

$$\text{subject to } \underline{w}^\dagger \underline{d} = 1 \tag{3}$$

where $\underline{d}$ is the focusing vector designed to steer the beam in the direction θ. This problem is a problem of minimization under constraint that can be solved using Lagrange multipliers. The optimal weights vector is therefore given by:

$$\hat{\underline{w}} = \frac{\mathbf{R_{xx}}^{-1}\underline{d}}{\underline{d}^\dagger \mathbf{R_{xx}}^{-1}\underline{d}} \tag{4}$$

In medical ultrasound imaging, this set of weights is computed for the received data for each transmission line at each depth. Eventually, they are applied to the per-channel received data such as $y(t) = \underline{\hat{w}}^{\dagger}\underline{x}(t)$ which replace the conventional delay-and-sum (DS) beamformer. Note that the Capon's beamformer corresponds to a narrow-band beamforming since equation (4) is derived for a given frequency.

3. IMPLEMENTATION OF THE FAB ON ULTRASOUND DATA

3.1. Simulated data set

All tests are performed using a simulated data set simulated with Field II [2]. The probe used is a 64 elements phased array performing at $3\,\text{MHz}$. 100 transmission lines are used to insonify the medium from $-15\,\text{d}^{\circ}$ to $+15\,\text{d}^{\circ}$. The simulated ultrasonic medium represents a target point scatterer next to a cyst. On figure (1) is represented the corresponding scan converted image. Note that the bright point target produces some smearing inside the cyst which is precisely the kind of artifact we want to reduce by using the FAB. This simulated data set is realistic since it corresponds to clinical flaws we want to reduce. To implement the algorithm, the analytic per-channel geometrically aligned signals are used.

3.2. First implementation of the FAB

Initially, the per-channel signals were beamformed using the FAB as defined in equation (4). The array output covariance matrix was estimated using the sample estimate:

$$\hat{\mathbf{R}}_{\mathbf{xx}} = \frac{1}{N}\sum_{i=1}^{N}\underline{x}_i\underline{x}_i^{\dagger} \tag{5}$$

where $\underline{x}_i$ is the i^{th} snapshot and N is the number of snapshots. Figure (2) shows the resulting beamformed scan converted data. We can observe that the FAB does not yield to satisfactory results. The image is entirely destroyed.

3.3. Coherence between signals

A key assumption of the FAB is that the interferers (off-axis signals) and the signal of interest (on-axis signal) are mutually non-coherent. This means that the phase difference between sources have to be random. Two signals are said to be coherent if one is a scaled and delayed replica of the other. In practice, in the case of coherent or highly correlated signals, the FAB is not able to cancel the interferences. In the medical ultrasound medium, we are actually dealing with coherent or highly correlated signals. Indeed, to insonify the medium a transmit pulse in sent into the body. The received signals are all replicates of this same transmit pulse being consequently highly correlated or even coherent.

3.4. Second implementation of the FAB: Spatial Smoothing preprocessing

To get round the correlation between sources, a preprocessing that creates an artificial "decorrelation" have to be applied. In array processing literature, the *spatial smoothing* preprocessing appears to be widely used to cope with highly correlated signals. This preprocessing was introduced in 1985 by Shan and Kailath [3]. It performs a spatial averaging by subdividing the array into smaller subarrays and estimates the array output correlation matrix by averaging the subarrays output correlation matrices. The implementation of the FAB is performed as follow:

1. divide the M sensors array output $\underline{x}(t)$ into L overlapping subsets of size k, $L = M - k + 1$:

$$\begin{aligned} z^1(t) &= [x_1(t)\ldots x_k(t)]^T \\ z^2(t) &= [x_2(t)\ldots x_{k+1}(t)]^T \\ &\vdots \\ z^L(t) &= [x_L(t)\ldots x_M(t)]^T \end{aligned} \tag{6}$$

2. compute the subarray sample covariance matrices:

$$\hat{\mathbf{R}}^{SA^l} = \frac{1}{N}\sum_{j=1}^{N}\underline{z}_j^l\underline{z}_j^{l\dagger} \tag{7}$$

   where, $\underline{z}_j^l$ is the j^{th} snapshot received on subarray l.

3. compute the spatially smoothed covariance matrix:

$$\hat{\mathbf{R}}^{SM} = \frac{1}{L}\sum_{l=1}^{L}\hat{\mathbf{R}}^{SA^l} \tag{8}$$

4. for each subgroup of sensors:

   (a) compute the $(1,k)$ weights vectors as in (4):

$$\underline{w}^{SA^l} = \frac{\mathbf{R}^{SM^{-1}}\underline{d}^l}{\underline{d}^{l\dagger}\mathbf{R}^{SM^{-1}}\underline{d}^l} \tag{9}$$

   where $\underline{d}^l$ is the corresponding focusing vector

   (b) apply the weights and sum as follow:

$$s^{SA^l} = \underline{w}^{SA^l\dagger}\underline{z}^l \tag{10}$$

5. compute the final sum:

$$y(t) = \frac{1}{L}\sum_{l=1}^{L}s^{SA^l} \tag{11}$$

On figure (3) are represented the scan converted data of the received signals beamformer with the spatial smoothing preprocessing. We can observe on figure (3) that with spatial smoothing preprocessing, the fully adaptive beamformer perform very well and by comparing with figure (1) that the size of the smearing inside the cyst is reduced.

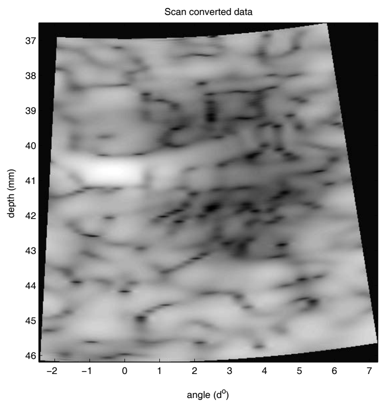

Fig. 1. Scan converted simulated data

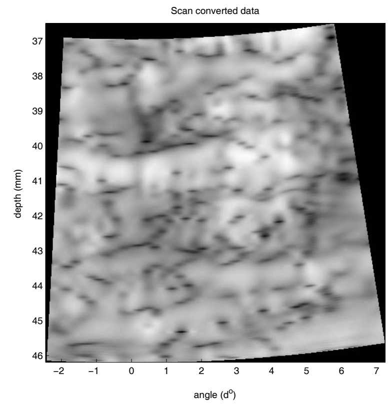

Fig. 2. First implementation of the FAB

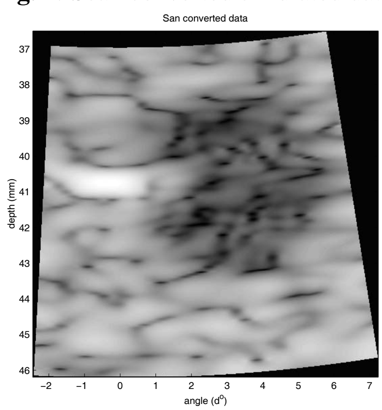

Fig. 3. FAB combined with the spatial smoothing preprocessing

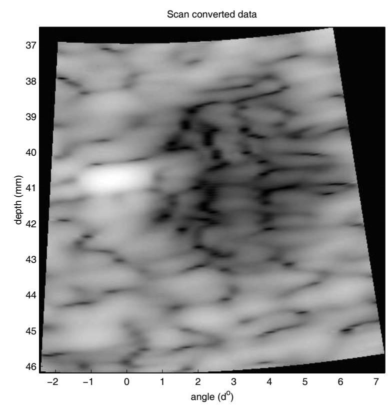

Fig. 4. FAB with spatial smoothing preprocessing and the use of the received data from consecutive transmission lines

3.5. Third implementation of the FAB: use of received signals from consecutive transmission lines

A complementary preprocessing is then devised to give a better decorrelation to the received signals and to increase the amount of data in the sample covariance matrix estimate. This preprocessing uses the received data of previous and following transmission lines all focused in the direction of interest. Each subarray covariance matrix is then estimated as follow:

$$\hat{\mathbf{R}}^{\mathbf{SA^i}} = \frac{1}{N_T} \sum_{T_i=1}^{N_T} \frac{1}{N} \sum_{j=1}^{N} \underline{z}_j^{lT_i} \underline{z}_j^{lT_i \dagger} \qquad (12)$$

where N_T is the total number of transmission line used, $\underline{z}_j^{lT_i}$ is the j^{th} snapshot for the transmission line T_i received by the subarray l and N is the number of snapshots. N_T being odd, the transmission line of interest is $\lfloor \frac{N_T}{2} \rfloor$. The FAB is implemented with this scheme combined with the spatial smoothing preprocessing. On figure (4) are represented the corresponding scan converted image using the received data of 15 transmission lines. We can observe that this configuration performs a lot better than the previous configuration represented on figure (3). The smearing inside the cyst is greatly reduced. The point target resolution is improved. This ultimate implementation will be used throughout to access the results and compare with the conventional scheme.

4. RESULTS ASSESSMENTS

4.1. Contrast-like and gain computation

To assess the enhancement realized, a contrast-like computation and a gain wrt. the classical DS beamformer are devised. Using the compressed data before scan conversion, two zones are defined. A zone L_1 which is included in the bright point target part of the image and a zone L_2 inside the cyst which includes the whole smearing on the image beamformed with the DS beamformer. The contrast computation is defined as follow:

$$C = \frac{\sum_{i \subset L_1} I(\mathrm{pix}_i)}{\sum_{j \subset L_2} I(\mathrm{pix}_j)} \qquad (13)$$

where $I(\text{pix}_k)$ is the intensity of the pixel k. The gain wrt. to the DS beamformer is assessed in dB as follow:

$$G = 20 * \log \frac{C_{FAB}}{C_{DS}} \qquad (14)$$

where C_{DS} is the contrast computed with the classical DS beamformer and, C_{FAB} is the contrast computed for the FAB.

The spatial smoothing introduces an apodization by processing and averaging on subarrays. For that reason, the gain for the FAB scheme is compared with the DS beamformer performed on subarrays to determine if the enhancement is only due to the spatial smoothing. The gain for the FAB is equal to 2.7 dB and the gain for the DS beamformer on subarrays is equal to 1.6 dB. The FAB clearly performs better and the smearing is more reduced.

4.2. Smearing reduction and resolution assessment

To assess in a more precise way the smearing reduction and the resolution, the compressed data before scan conversion, that is the compressed beamformed received data, are represented on figure (5). The top graphic represents the compressed received data for the transmission line at angle 1.5 d° which corresponds to the brightest smearing inside the cyst. The bottom one represents the compressed received data at a depth of 40.8 mm corresponding to the position of the bright point target in depth. On the top graphic, we can observe that at the exact position of the smearing, between 40 and 42 mm, the contribution of the off-axis energy is greatly reduced with the FAB. Indeed, the brightest point within the cyst corresponds to 47.5 dB with the DS beamformer, 42 dB with the DS on subarrays and 35 dB with the FAB. The bottom graphic shows that averaging over subarrays degrades the resolution. Indeed, the DS beamformer on subarrays gives a worst resolution than the DS beamformer. Nevertheless, the FAB using the spatial smoothing improves the resolution. This comes from the benefit of averaging in the estimation of the array output covariance matrix over the received data of consecutive transmission lines all focused in the direction of interest. We can also observe from this graphic that the smearing is removed on the left to the point target and greatly reduced on its right.

5. CONCLUSION

We have proposed to adapt the Capon's version of the FAB to the field of ultrasound imaging for the reduction of image artifact in the presence of off-axis energy. Using simulated data which give a very good approximation of the linear propagation in medium, we have first illustrated the problem of smearing of bright points and illustrated the effect of several adaptation of the algorithm. As the original algorithm was developed for non correlated signals we have proposed an adaptation based on the spatial smoothing. In order to further decorrelate the received signals, the autocovariance matrix is averaged over the received data from several transmission schemes. The results show that FAB can be successfully implemented for medical ultrasound beamforming. With the peculiar preprocessing, the FAB greatly reduces the contribution of off-axis energies and improves the target resolution. These results are promising as for the application of adaptive array processing techniques in medical ultrasound.

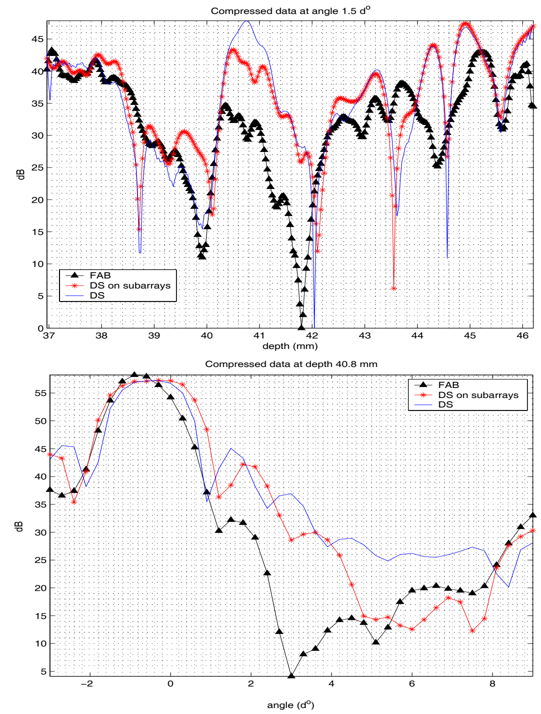

Fig. 5. Compressed data at angle 1.5 d° and at depth 40.8 mm for the FAB, the DS on subarrays and the DS beamformer

6. REFERENCES

[1] J. Capon, "High resolution frequency-wavenumber spectrum analysis," Proc. IEEE, vol. 57, no. 8, pp. 1408–1418, 1969.

[2] J. A. Jensen, "Field: A program for simulating ultrasound systems," Med. Biol. Eng. Comp., vol. 34, Part 1, pp. 351–353, 1996, 10th Nordic-Baltic Conference on Biomedical Imaging.

[3] T. J. Shan and T. Kailath, "Adaptive beamforming for coherent signals and interferences," IEEE Trans. on Acoustics, Speech and Signal Processing, vol. 33, no. 3, Jun. 1985.