

Low Complexity Adaptive Beamformer for Active Sonar Imaging

Brilliant mind at work! >>>>

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Abstract—We have studied the low complexity adaptive (LCA) beamformer in active sonar imaging. LCA can be viewed as either a simplification of the minimum variance distortionless response (MVDR) beamformer, or as an adaptive extension to the delay and sum (DAS) beamformer. While both LCA and MVDR attempt to minimize the power of noise and interference in the image, MVDR seeks the optimal solution by estimating and inverting the array's spatial covariance matrix, while LCA selects the best performer from a predefined set of sensor windows.

We show that a robust MVDR implementation typically creates windows spanning between the rectangular and Hamming. We let LCA select from a set of Kaiser windows with responses in this span, and add some steered variations of each. We limit the steering to roughly half the -3 dB width of the window's amplitude response. Using experimental data from the Kongsberg Maritime HISAS 1030 sonar we find that LCA and MVDR produce nearly identical images of large scenes, both being superior to DAS. On point targets LCA is able to double the resolution compared to DAS, or provide half that of MVDR. This performance is achieved with a total of 6 windows; the rectangular and Kaiser window with $\beta = 5$, in unsteered version, and left and right steered to the steering limit. Slightly smoother images are produced if the window count is increased to 15, but past this we observe minimal difference. Finally we show that LCA work just as well if Kaiser windows are substituted with trigonometric ones.

All our observations and experiences point to LCA being very easy to understand and manage. It simply works, and is surprisingly insensitive to the exact type of window function, steering amount, or number of windows. It can be efficiently implemented on parallel hardware, and handles any scene without the need for parameter adjustments.

Index Terms—Beamforming, adaptive beamforming, MVDR, LCA, sonar, active, complexity.

This analogy is awesome! So easy to understand

I. INTRODUCTION

THE best adaptive sonars are found in nature. Bats, for instance, use a high frequency sonar to detect, identify and track prey with amazing precision in caves amongst a myriad of other bats. Active human made sonars have little to no adaptability on transmit, but several adaptive methods have been investigated post process the received data. Perhaps the best studied method for reconstructing a sonar image is the minimum variance distortion-less response (MVDR) beamformer [1]. It adapts the sonar array's response to minimize the influence of noise and interference in the final image.

In many cases MVDR can improve the contrast and resolution of active sonar images compared to conventional

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static methods [2]–[4]. However, while the computational complexity of conventional beamformers are linear with the number of channels, $O(M)$, MVDR is at $O(M^3)$. This is because MVDR relies on estimating and inverting a covariance matrix. In sonar systems with less than 32 channels the complexity can be reduced and the implementation accelerated significantly using graphics computing units (GPUs) [5]. For larger systems the inversion step dominates the computation. This can be dealt with by approximating the full covariance matrix with a small one using space reduction techniques such as beamspace processing [6], or the closely related principal component analysis (PCA) method [7]. Another method is to assume spatial stationarity to form more easily invertible Toepliz matrices [8]. However, the mentioned methods are still relatively slow compared to DAS.

A much faster and simpler alternative to MVDR is the Low Complexity Adaptive (LCA) beamformer. Based on an idea by Vignon [9], it was first introduced by Synnevåg *et al.* in clinical medical imaging [10], who demonstrated its ability to obtain very similar image quality to MVDR in systems with focused transmit beams. LCA applies a set of predefined windows, or apodization weights, and selects the one offering the best sidelobe suppression. It relies on the same optimization criterion as MVDR, thus may be considered a version of MVDR with a reduced window solution space. Alternatively, it may be viewed as a multi-apodization technique. One such method is described by Stankwitz *et al.* in radar imaging [11], where the best out of 2 or 3 windows are selected. However, LCA is different in that it typically selects from more windows and allow micro-steered variations of them. This gives LCA an adaptive freedom that is somewhere in between that of traditional multi-apodization techniques and MVDR.

Synnevåg *et al.* suggested using a window set comprised of rectangular, Kaiser (or Kaiser-Harris) and inverted Kaiser functions. In total he made LCA choose from 12 unique windows, 6 of which were micro-steered variants of a fairly wide Kaiser window, and with the rectangular window included. This was motivated by the desire to use wide windows with maximum sidelobe suppression near the receiver, and narrow windows at greater depths for maximum sensitivity and depth penetration. While achieving good results, it was not made clear how many windows LCA needs, or how they ideally should be steered. Also, it is not apparent how LCA performs in sonar systems where the transmit beam is unfocused.

In this study apply LCA to active sonar imaging. We use variations of the parametric Kaiser window, but also compare it to the trigonometric window function. We extend Synnevåg's work by steering all our windows and not just some, and

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demonstrate how LCA's performance is affected by type and number of windows included. Our results are obtained using experimental data from the 32 element Kongsberg Maritime HISAS 1030 synthetic aperture sonar (SAS), which operates at 100 kHz with an element beamwidth of 23°.

Our results show that MVDR, when adapted to work in active sonar imaging, computes weights with responses that tend to be symmetric and steered within a fraction of the window's -3dB resolution. When letting LCA choose from Kaiser windows with similar responses, we obtain images with improved noise suppression and resolution. The resolution gain is made predictable by limiting the maximum steering to a fraction of the window's -3 dB width. Overall, LCA produces images that are similar to MVDR, but with a resolution in between that of DAS and MVDR. LCA is also inherently robust, easy to implement, and fairly easy to understand.

This article is outlined as follows: In Section II we offer a gentle introduction to beamforming. Then we move on to adaptive beamforming and describe the MVDR and LCA methods III and IV, respectively. We use LCA with the Kaiser window which we describe in IV-A, explain how we steer it in IV-B, and by how much in IV-C. Finally, we add some remarks on using the trigonometric window instead of Kaiser in IV-D, and of sampling considerations in IV-E. Results and discussion are provided in Section V, where we study MVDR's windows to find suitable LCA ones in V-A, assess the range of window types and steering in V-B, determine the number of windows needed in V-C, and add a note on computational complexity in V-E. Finally, we conclude in VI.

II. RECEIVE BEAMFORMING

estimating? A sonar image is formed by estimate source locations and amplitudes. For this purpose a spatial bandpass filter is applied to the backscattered wavefield data. The filter is called an array processor, or receive beamformer. The basic principle is to apply delay and weights to the sensor channels before summing them up, chosen such that signals from the location of interest are summed coherently, while other sources sum incoherently.

Assume that the wavefield has been sampled by an M element uniform linear array, and that the signal signature has been removed by a matched filter. Let $x_m[\theta, n]$ be the delayed data from the m th channel, where the θ and n are the azimuth angle and range sample of the focus point, respectively. Each angle θ will be processed independently, so to simplify notation we will assume the dependence on θ to be implicit from now on.

The output $z[n]$ of a beamformer is defined as the weighted sum of all the delayed data samples:

$$z[n] = \mathbf{w}^H[n] \mathbf{x}[n] = \begin{bmatrix} w_0[n] \\ w_1[n] \\ \vdots \\ w_{M-1}[n] \end{bmatrix}^H \begin{bmatrix} x_0[n] \\ x_1[n] \\ \vdots \\ x_{M-1}[n] \end{bmatrix}, \quad (1)$$

where w_m is the weight factor assigned to channel m . A weight set is commonly called a window, apodization or taper function. Applying a window that trails off towards

the edges improves noise suppression at the cost of reduced resolution [12]. Real windows lead to symmetric responses, while complex weights allow asymmetric responses.

Conventional beamformers all have static weights. The reference method is the delay-and-sum (DAS) beamformer, also known as the backprojection algorithm. It delays each pixel into focus, then applies a suitable window, and finally sums the data. The virtue of DAS is its simplicity, robustness to parameter errors, linear processing of the image and the ease of which it can be implemented on parallel hardware.

Adaptive beamformers are dynamic and seek to adjust the array response to better fit the incoming wavefield. This may be achieved by allowing either the weights or delays to change, or both. One of the most extensively studied of these methods is the minimum variance distortion-less response (MVDR) beamformer.

III. MVDR

MVDR seeks to minimize the output variance of the beamformer, under the constraint of a unity gain in some desired direction ϕ [1]. With the assumption of zero mean data this can be formulated as:

$$\underset{\mathbf{w}[n]}{\operatorname{argmin}} E\{|z[n]|^2\} = \underset{\mathbf{w}[n]}{\operatorname{argmin}} \mathbf{w}[n] \mathbf{R}[n] \mathbf{w}^H[n] \quad \text{subject to } \mathbf{w}^H[n] \mathbf{a}_\phi = 1. \quad (2)$$

Here \mathbf{a}_ϕ is a steering vector, $E\{\cdot\}$ is the expectation operator, and $\mathbf{R}[n] = E\{\mathbf{x}[n]\mathbf{x}^H[n]\}$ is the spatial covariance matrix for the full array. This is a convex optimization problem with the solution:

$$\mathbf{w}[n] = \frac{\mathbf{R}^{-1}[n] \mathbf{a}_\phi}{\mathbf{a}_\phi^T \mathbf{R}^{-1}[n] \mathbf{a}_\phi}. \quad (3)$$

The problem lies in estimating and inverting this spatial covariance matrix. We have described the exact steps in [5]: To avoid signal cancellation we apply spatial averaging by computing a mean covariance matrix from a set of subarrays with length L [13], for true speckle statistics we perform temporal averaging over $N_k = 2K + 1$ temporal samples [14], and to improve robustness to parameter errors we add ϵ percent diagonal loading [15], [16]. These steps are also needed to ensure that the covariance matrix is numerically well conditioned and hence invertible.

IV. LCA

A much less complex alternative to MVDR is the low complexity adaptive (LCA) beamformer. It iterates through a set of P windows and selects the window p that best fulfills the minimum variance criterion:

$$\underset{p}{\operatorname{argmin}} E\{|z_p[n]|^2\} = \underset{p}{\operatorname{argmin}} E\{|\mathbf{w}_p^H \mathbf{x}[n]|^2\} \quad \text{subject to } \mathbf{w}^H \mathbf{a}_\phi = 1. \quad (4)$$

Note how closely LCA is related to the MVDR definition in (2). The optimization criterion and constraint is the same, but LCA has a finite and discrete solution space for the weights. As will be demonstrated in section V-A, LCA will

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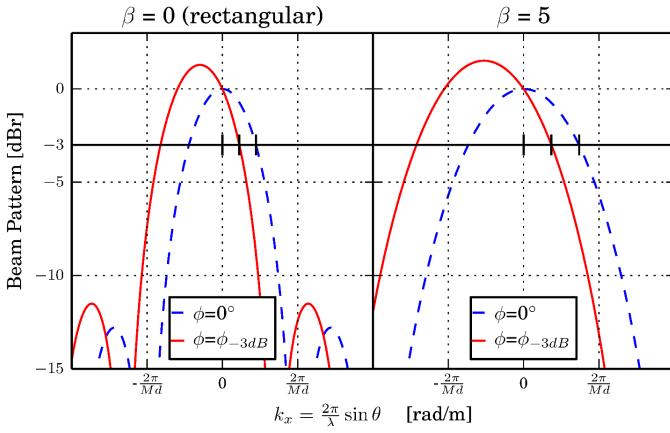


Fig. 1. Each Kaiser window is steered in the interval $\phi = [0, \phi_{-3dB}(\beta)]$. The angle $\phi_{-3dB}(\beta)$ is the amount of steering needed for the steered response to have a -3dB crossing that is exactly half that of the unsteered window. With each window steered this way we expect the resolution gain to remain predictable and independent of β , and we also effectively constrain the white noise gain of the beamformer.

perform similarly to MVDR because a robustified MVDR implementation seems to be constrained to window functions similar to the ones we let LCA choose from.

In practice, we estimate the beamformer output power as

$$E\{|z[n]|^2\} = \frac{1}{N_k} \sum_{n'=-K}^{n+K} |z[n']|^2$$

which computes the sample power average over $N_k = 2K + 1$ temporal samples. This is the same temporal averaging method we use for MVDR. In our case the bandwidth of our matched filtered signal is a just few samples long, hence $K = 1$ will be used for both MVDR and LCA throughout this work.

Since pixels are correlated laterally, we can include a weighted combination of these as well to improve the variance

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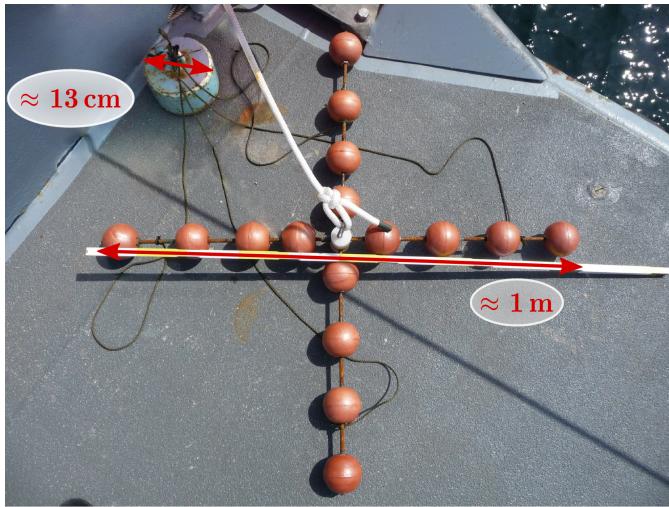


Fig. 2. One of the objects used to test the beamformers is a 1 m by 1 m cross attached to an anchor with a diameter of approximately 13 cm. Source image courtesy of Bundeswehr Technical Center for Ships and Naval Weapons, Maritime Technology and Research (WTD 71).

ummmmm.... nice math! I'll take your word for it! :p

estimation:

$$E\{|z[x, n]|^2\} = \frac{1}{N_x N_k} \sum_{x'=-X}^{x+X} \sum_{n'=-K}^{n+K} w_{\text{prf}}[x', n'] |z[x', n']|^2 \quad (5)$$

where $N_x = 2X + 1$ is the number of azimuth lines to average over, and $w_{\text{prf}}[x', n']$ is a normalized 2 dimensional weight function. However, we observed no visual improvement doing this, and the effect of micro-steered windows is hard to predict. Henceforth no lateral averaging will be applied.

A. Window function: Kaiser

As will be demonstrated in upcoming sections, the LCA beamformer works very well with windows generated from the Kaiser-Bessel function. We will express it in vector form as:

$$\mathbf{f}_\beta = \begin{bmatrix} f_0(\beta) \\ \vdots \\ f_{M-1}(\beta) \end{bmatrix} \quad (6)$$

where

$$f_m(\beta) = \frac{I_0\left(\pi\beta\sqrt{1 - \left(\frac{2m}{M-1} - 1\right)^2}\right)}{I_0(\pi\beta)} \quad (7)$$

and I_0 is the zeroth order modified Bessel function of the first kind:

$$I_0(x) = \sum_{a=0}^{\infty} \left[\frac{\left(\frac{x}{2}\right)^a}{a!} \right]^2. \quad (8)$$

The Kaiser-Bessel window is near optimal in the sense of having its peak energy concentration around $\theta = 0^\circ$, for a given space-bandwidth product specified with the parameter β :

$$\beta = \frac{TB}{2}, \quad (9)$$

where T in our case is the spatial extent of the window and B is its bandwidth. Adjusting β changes the trade-off between mainlobe width and sidelobe level. When $\beta = 0$ the window becomes rectangular, while at large values ($\beta > 5$) the window converges to a Gaussian both in time and frequency. This class of windows is generally considered well suited for separating closely spaced sources with amplitudes of a high dynamic range [12], they are easy to make, and they are optimal for any value of β .

B. Steering

Adding slightly steered versions of each window to the window database gives LCA greater flexibility in searching for an optimal window. A Kaiser window \mathbf{f}_β steered to the angle ϕ can be expressed as

$$\mathbf{w}_{\beta, \phi} = \frac{\mathbf{f}_\beta^H \text{diag}(\mathbf{a}_\phi)}{\mathbf{f}_\beta^H \mathbf{a}_\phi} \quad (10)$$

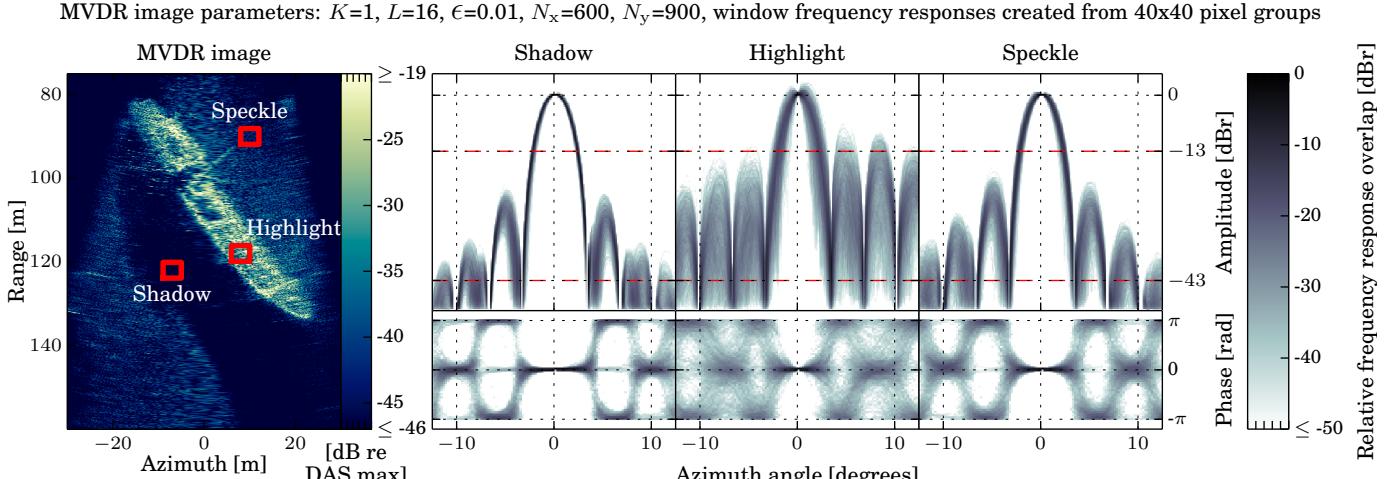


Fig. 3. Determining LCA window type: MVDR image with typical frequency responses for windows used in various pixel regions.

Left: MVDR sectorscan image of the oiltanker Holmengraa, with the pixel groups are indicated with red boxes.

Right: MVDR window amplitude and phase responses computed from 40x40 pixel groups in the shadow, highlight and speckle region of the image. The responses are overlayed each other and the amount of overlap is colored using a logarithmic scale. The dashed red lines at -13 dB and -43 dB marks the peak sidelobe levels of an unsteered rectangular and Hamming window, respectively. Note how the responses are more or less symmetric, with very little steering in the shadow, moderate steering in speckle and steering within roughly 3 dB in highlight. The phase varies most in the highlight region where we see the highest contrast.

where $\text{diag}(\mathbf{a}_\phi)$ is a diagonal matrix constructed from the steering vector \mathbf{a}_ϕ :

$$\mathbf{a}_\phi = \begin{bmatrix} 1 \\ e^{-j\frac{2\pi d}{\lambda} \sin(\phi)} \\ \vdots \\ e^{-j\frac{2\pi(M-1)d}{\lambda} \sin(\phi)} \end{bmatrix}. \quad (11)$$

Here d is the element spacing, λ is the wavelength and ϕ is the steering amount. The normalization factor $\mathbf{f}_\beta^H \mathbf{a}_\phi$ is the reciprocal of the window's coherent gain. It ensures unit gain in the direction of interest as required by (4). Since the signal-to-noise ratio is constant for a specific window (same β -value), this normalization also proportionally increases the incoherent noise gain.

The window database we will construct will contain N_β Kaiser windows with unique β -values, each being steered in N_ϕ different directions. This gives us $N_w = N_\beta N_\phi$ unique windows.

C. Steering bounds

Each window's response is constrained to unit gain in the look direction. Hence, when it is steered the white noise gain must increase and the the signal-to-noise ratio decrease, as shown in Fig. 1. To limit this we place an upper bound to the steering, chosen such that wide windows is allowed to be steered more than narrow ones. We call this upper bound for steering $\phi_{3dB}(\beta)$, and define it as the steering angle needed for the steered response to have a -3 dB crossing that is exactly half that of the unsteered window. Using a numerical search for the steering angle ϕ that fulfilled this criterion for a wide range of β -values, we obtained a third degree polynomial fit

to these points:

$$\phi_{3dB}(\beta) \approx -0.002894\beta^3 + 0.02451\beta^2 - 0.01308\beta + 0.2980 \quad (12)$$

Henceforth any steering will be specified relative to this upper bound. With each window steered this way we expect the resolution gain to remain predictable and independent of β , and we also effectively constrain the white noise gain of the beamformer.

D. Trigonometric windows

While we focus on using LCA with Kaiser windows, we will for completeness compare the performance with that of using trigonometric windows. This is defined as:

$$f_m(\alpha) = \alpha - (1 - \alpha) \cos\left(\frac{2\pi m}{M - 1}\right) \quad (13)$$

where we apply the constraint $\alpha \in [0.5, 1]$ to avoid windows with negative coefficients. Steering is applied as in (10), and the α -value that halves the 3 dB distance is found using the method described in section IV-C:

$$\phi_{3dB}(\alpha) \approx -2.214\beta^3 + 6.084\beta^2 - 5.710\beta + 2.136. \quad (14)$$

E. Oversampling

The ultimate goal of adaptive beamformers is to take the information available in the wavefield and use it to either improve image resolution, sidelobe suppression, or preferably both. This non-linear processing increases the image bandwidth and introduces a need for a sampling rate higher than the Nyquist rate. For MVDR a lateral oversampling factor of 10 compared to the Nyquist rate is often needed to ensure minimal spatial shift-variance in source amplitude [17].

Since LCA operates with the same optimization criterion as MVDR, we will be using approximately a factor 8 lateral

more nice math! :D

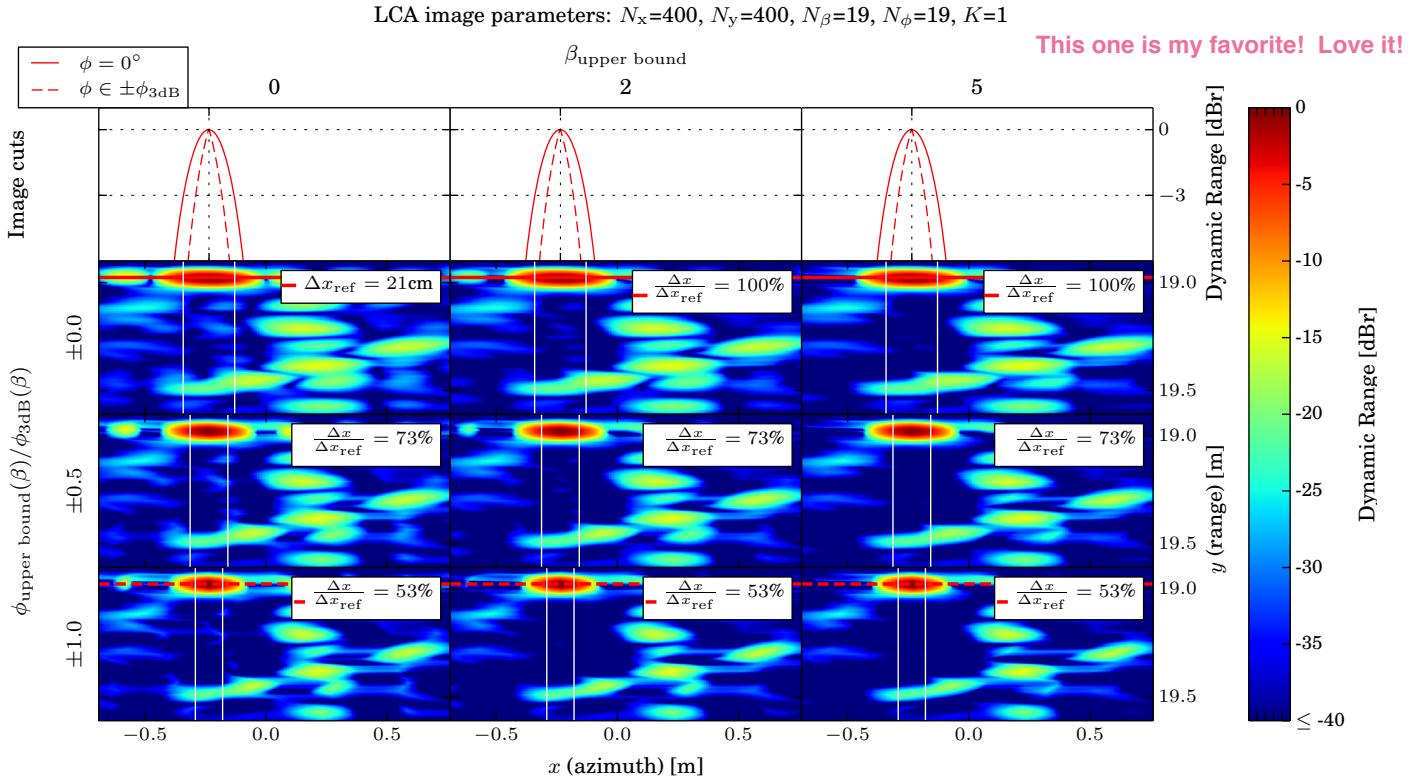


Fig. 4. Determining Kaiser parameter boundaries: LCA images of the cross and anchor created with a large and equal size window database, but where the upper bounds for β and ϕ is varied. The upper left image is equal to DAS with a rectangular window. For all images we measure the lateral distance Δx between the two -3dB points of the anchor (red object). These are specified relatively to the reference distance Δx_{ref} from the upper left DAS image.
Upper bound β : Observe that LCA gets better at suppressing sidelobes in the image as we increase the upper bounds for β . Fig. 3 suggests that MVDR tend to choose windows with levels lower than that of Kaiser with $\beta = 2$, but here we observe further improvement going to $\beta = 5$.
Upper bound ϕ : As we increase the upper bound of the steering ϕ , we also increase the lateral image resolution.

oversampling for both beamformers. The images appear more visually pleasing and detailed up to 8. We consider an absolute minimum to be 2, due to the non-linear nature of delaying pixels that isn't strictly in the far field, and of displaying the absolute value of the pixels on a decibel scale. In [Media Movie 1](#) we visualize the effect of changing the lateral oversampling factor on a set of LCA images. Upon display the images are all bilinearly upinterpolated to the same size.

V. RESULTS AND DISCUSSION

To test the performance of the MVDR and LCA beamformers, we have processed data acquired by the Kongsberg Maritime HUGIN AUV carrying their 32 element HISAS1030 sonar [18]. It is a high resolution synthetic aperture sonar with 1.2 m array length, 100 kHz operating frequency, 30 kHz bandwidth and 23° receiver element beamwidth.

Two different scenes will be studied. One of the 1500 DWT oil tanker wreck Holmengraa lying at a slanted seabed at 77 m depth outside of Horten, Norway [19]. It measures 68 m by 9 m and fills most of the highlighted sector. This data was collected by the Norwegian Defense Research Establishment and Kongsberg Maritime. The other scene is of an 1 m by 1 m iron cross, connected to a an anchor with 13 cm diameter (Fig. 2). This data was collected by the Bundeswehr Technical Center for Ships and Naval Weapons, Maritime Technology

and Research (WTD 71). Both scenes are imaged in sectorscan mode.

In the image reconstruction we have run MVDR with subarray length $L = 16$ and $\epsilon = 1\%$ diagonal loading. Both MVDR and LCA was run with $K = 1$ temporal averaging. This is a fairly aggressive yet stable set of parameters [14].

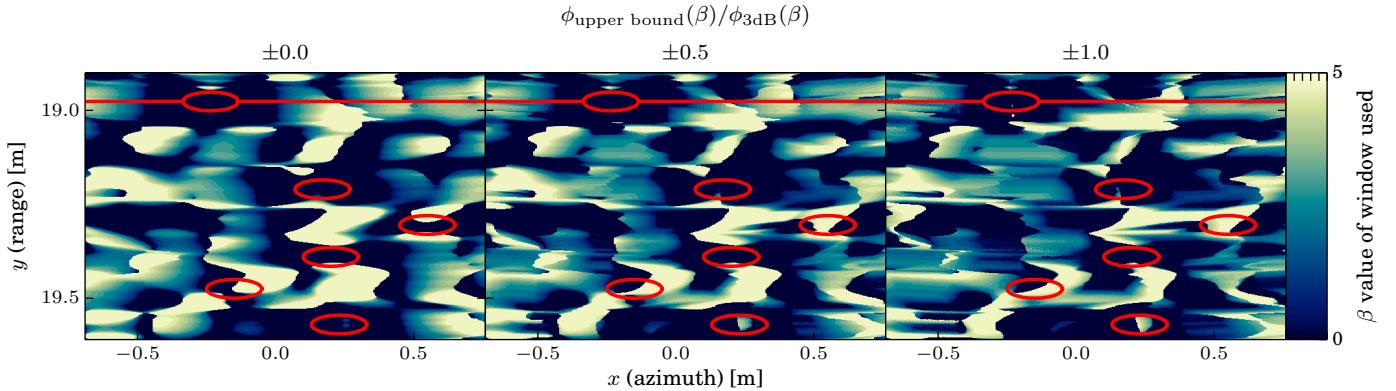
The results will be presented in the following order: In section V-A we discuss typical window responses computed by MVDR, and hypothesize that these can be mimicked by Kaiser windows. In section V-B we determine sensible boundaries for the Kaiser parameter β and window steering ϕ . In section V-C we discuss how many window variations are needed for LCA to perform well.

A. LCA window function

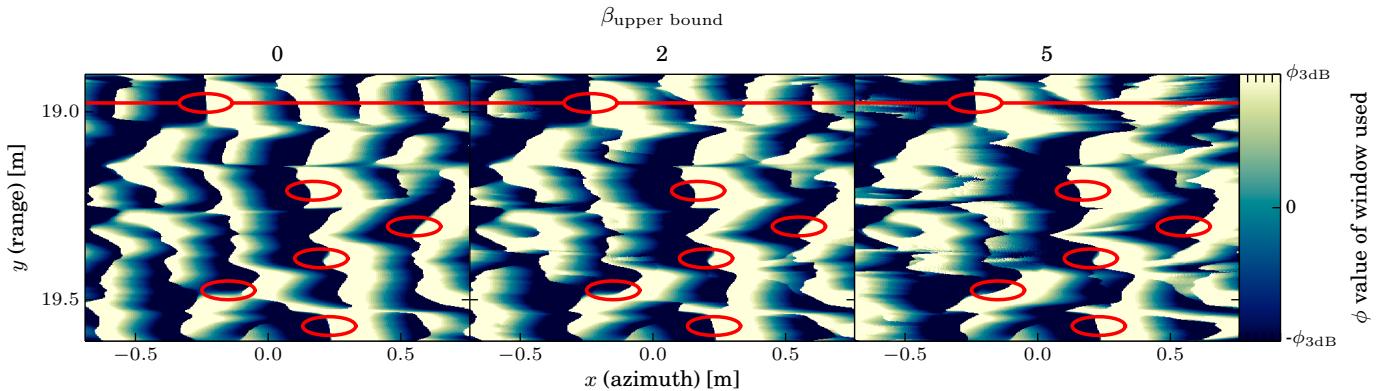
lose one with

Assuming that a robust MVDR is the reference method we want LCA to perform similarly to, it seems sensible to create a window database for LCA with responses similar to the ones that MVDR computes. We study this in Fig. 3, where we present the typical amplitude and phase responses that MVDR creates for shadow, speckle and highlight regions of the Holmengraa scene.

Observe from Fig. 3 that MVDR seems to prefer symmetric window responses, even if it is free to choose non-symmetric ones. The symmetry is most predominant in shadow and



(a) β -values of the Kaiser window chosen for each image pixel. Note how LCA prefers a narrow response ($\beta = 0$) on the anchor, and on other strong sources with little lateral interference. On the sources where lateral interference is present it chooses the widest response with the best sidelobe suppression.



(b) ϕ -values of the Kaiser window chosen for each pixel. On strong sources LCA selects windows that are steered away from the source. This is what improves the FWHM measurement in Fig. 4.

Fig. 5. Kaiser windows chosen for each pixel in the image. The underlying image is the one shown in Fig. 4, with the same parameters. The location of the anchor, cut line and main scatter locations of the cross is marked in red.

speckle regions, while in highlight the windows are approximately symmetric within the illuminated sector of the seafloor. We have observed this symmetry to be a side-effect of the averaging steps needed to build the sample covariance matrix, which are required for MVDR to operate in near snapshot mode in an active system. The peak sidelobe levels of the MVDR windows are mostly between -13 dB and -43 dB. This corresponds to that of an unsteered rectangular and Hamming window, or an unsteered Kaiser window with $\beta = 0$ and $\beta = 2$, respectively.

From this we hypothesize that a good window database LCA can be made using a varied set of Kaiser windows. If they span a suitable range of β -values, and some steering variations are applied to each, we should have responses that resemble those in Fig. 3. The Kaiser window is easy to compute, is fairly insensitive to coefficient inaccuracies, and can create windows with shapes spanning from rectangular to Gaussian. It is also optimal in the sense of having its peak power concentration near the steering angle.

Unlike the method described by Synnevåg [10] we do not let LCA choose from inverted Kaiser windows. These have a mainlobe width narrower than that of the rectangular window, but at the expense of a very poor white noise gain. We have found that these windows hardly ever get used on experimental data, in particular steered versions of them. We can infer the

same from Fig. 3 by noting that the maximum sidelobe level rarely exceeds the rectangular window level of -13 dB.

[Media Movie 2](#) animates how Fig. 3 changes as a function of the MVDR subarray length L and temporal averaging K . At $L = 1$ the window responses are rectangular in all areas in the image. At $L = 2$ we observe window responses with slight amplitude variations in the highlight region, but with the phase being 0° in the illuminated seafloor sector. Already at $L = 2$ the MVDR is able to greatly suppress noise. This is a common observation; adding a little flexibility to adapt to the scene has a dramatic effect, but further allowing full flexibility is much less significant. The media file also shows that MVDR can be run with subarray sizes $L \in [M/2, 5M/8]$, but only with temporal averaging $K = 1$ or above.

B. Kaiser parameter β and steering ϕ

To determine a suitable range for the Kaiser parameter β and steering ϕ , we constructed large and equally sized window databases containing Kaiser windows with varied upper boundaries for β and ϕ . The lower boundaries were chosen as $\beta = 0$ and $\phi = 0^\circ$, which includes the rectangularly weighted DAS image. The resulting images are shown in Fig. 4. In each image we computed the lateral distance Δx between the -3 dB points of the anchor, with the reference Δx_{ref} being the rectangularly weighted DAS image. A forth

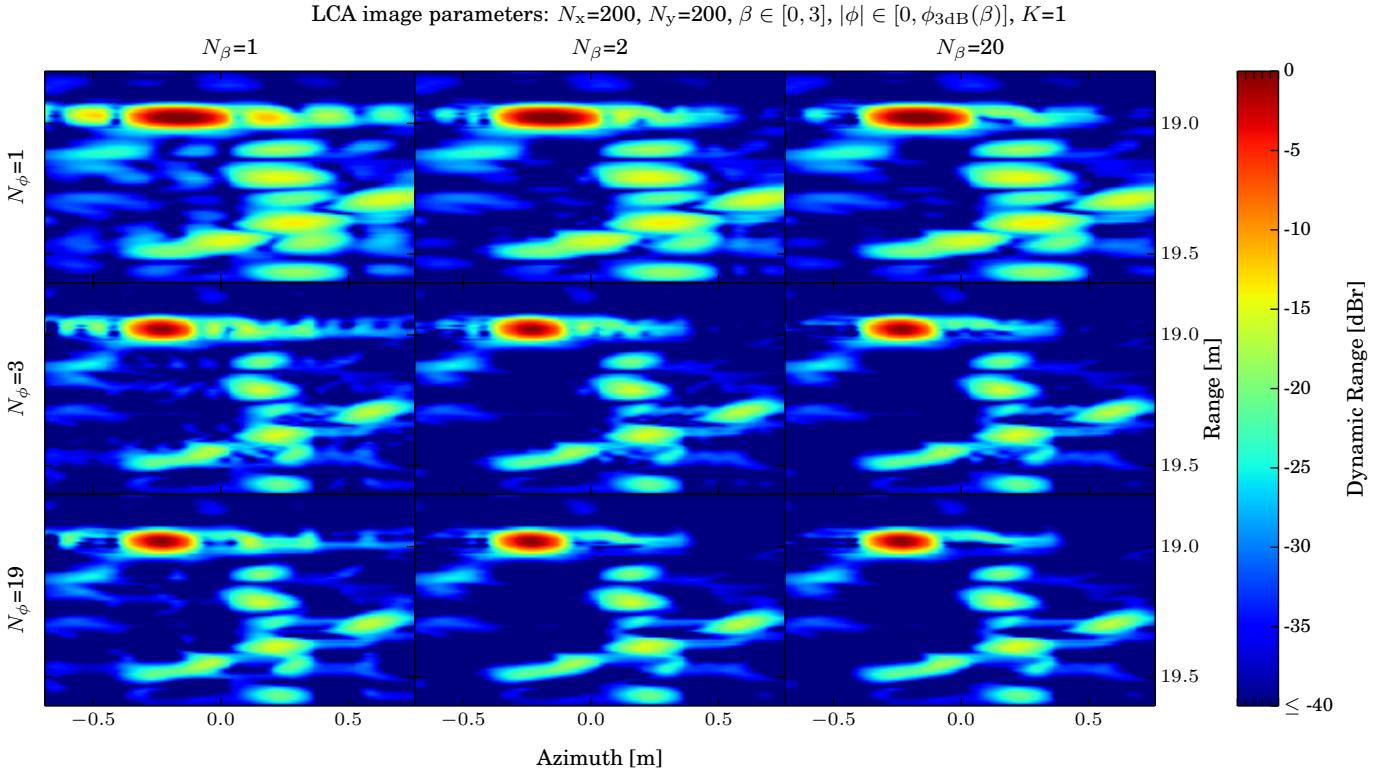


Fig. 6. LCA images using different window database sizes. The window boundaries are the same. The upper left image is identical to a rectangularly weighted DAS. Observe that sampling the β -range more finely increases the sidelobe suppression but leaves resolution unchanged. Adding more steering-variations improves both sidelobe suppression and resolution. However, using more than $N_\beta = 2$ window types and $N_\phi = 3$ steering angles makes minimal difference.

order polynomial fit was used in this computation. This measure is also commonly called the full width half maximum (FWHM). In the case of imaging a point scatter, it is closely related to the resolution of the system. For a rectangular window, for instance, the system resolution is approximately $\Delta \approx \text{FWHM}/0.89$ [12].

The LCA images in Fig. 4 demonstrate the effect of adjusting the upper bound of β and ϕ . As suggested by Fig. 3 we first attempted to use $\beta \in [0, 2]$. While this significantly improved sidelobe suppression, a slight further improvement was observed up to $\beta \in [0, 5]$. This can likely be explained by the need to compensate for the increased sidelobe levels caused by steering. No noticeable difference were observed for higher values than $\beta = 5$. The images also demonstrate that increasing the upper bound for steering ϕ improves the resolution of the strong scatterers. For this sonar the Rayleigh resolution is $\Delta \approx 0.0125$ radians (0.72°), so a point scatterer imaged at 19 m range with a rectangular DAS would have a lateral FWHM $\approx 0.125 \cdot 19 \text{ m} \cdot 0.89 = 21 \text{ cm}$. This is close to the FWHM of the anchor in the DAS image in Fig. 4, which means that the acoustic fingerprint of the anchor is similar to a point source. This suggests the anchor reflections to be specular and that we view its rounded side. As we increase steering to either 50% or 100% of the -3dB width, the FWHM drops to 73% or 53% to that of the rectangular window, respectively.

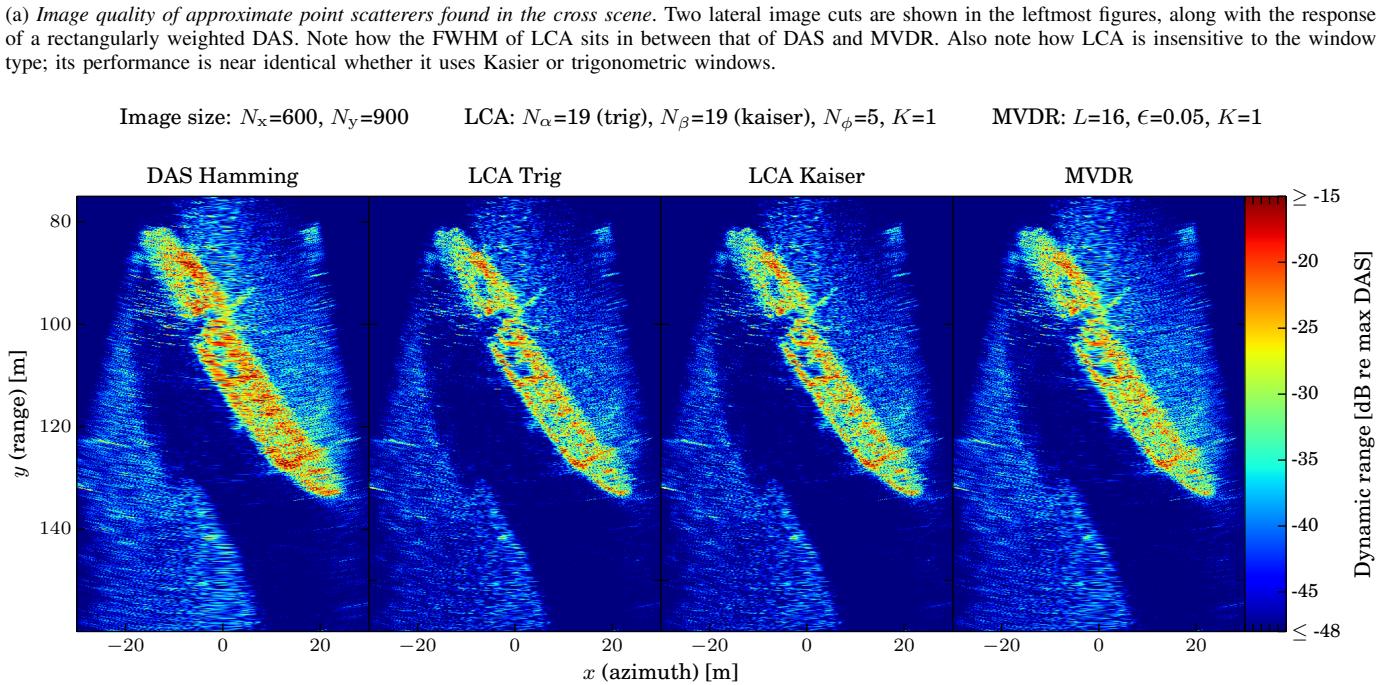
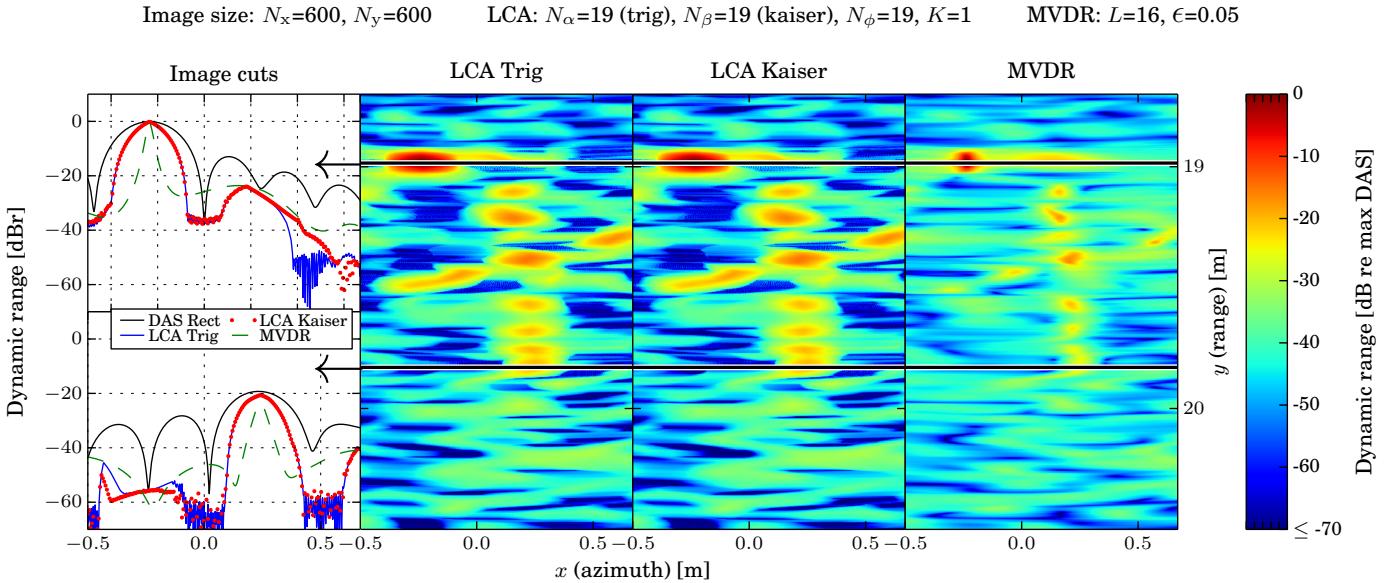
Fig. 5a and Fig. 5b illustrates which β and ϕ values LCA prefers for different regions in the image of the cross. Red

marker lines are used to pinpoint the cut line, location of the anchor and strong scatters on the cross. Observe that in the anchor region only narrow responses ($\beta = 0$) are used, which is the reason for the anchor FWHM being measured to the same value regardless of the upper bound of β in Fig. 4. On other scatterers with strong nearby lateral interference LCA prefers wider windows to suppress the interference. When allowed LCA prefers to steer windows away from the sources, but never exceed the $\phi_{3\text{dB}}(\beta)$ limit. When exceeding this bound we observed oscillation artifacts in the image.

C. Window database size

So far we have found it reasonable to use Kaiser windows in the range $\beta \in [0, 5]$, each steered within the range $|\phi| \in [0, \phi_{3\text{dB}}(\beta)]$. What remains is to determine the number of windows needed. We study this in Fig. 6, where we compared LCA images made from windows databases of different sizes, but with the same parameter boundaries. We included the results from using a single window ($N_\beta = 1$) and steering angle ($N_\phi = 1$), which corresponds to an unsteered rectangularly weighted DAS.

Observe that sampling the β -range more finely increases the sidelobe suppression but leaves resolution unchanged. Adding more steering-variations improves both sidelobe suppression and resolution. We can observe a major improvement going to $N_\beta = 2$ and $N_\phi = 3$, but minimal improvement by adding yet more windows.



D. Image quality

We compare LCA image quality to that of DAS and MVDR in Fig. 7. In Fig. 7a we display the images computed by LCA using Kaiser windows, LCA using trigonometric windows, and MVDR. Two lateral image cuts through all images are presented in the left plot. The images and their corresponding cuts are **nearly** identical for the LCA version with Kaiser windows and the one with trigonometric windows. Compared to DAS the LCA produces targets with an FWHM that lies in between that of DAS and MVDR.

In Fig. 7b we show full sector images of the Holmengraa wreck. We compare the images produced by a Hamming weighted DAS, by MVDR and by LCA with Kaiser or

trigonometric windows. All the adaptive beamformers produce a sharper and less noisy image than DAS, but the difference between LCA and MVDR is minimal. The LCA image produced with Kaiser windows appear identical to that from trigonometric windows.

E. Computational complexity

The computational complexity of MVDR is generally considered to be of $O(M^3)$. However, the implementation we are using is optimized so that building the spatial covariance matrix is of $O(N_k N_L L^2)$, and inverting it is of $O(L^3)$. We describe this implementation in [5], and a beampspace version in [6], where we optimize if for a graphics processing unit

(GPU) for nearly two orders of magnitude speed increase compared to a straightforward C implementation. However, MVDR is not ideal for GPUs due to the complex data dependencies present in the covariance computation, and at best we only managed to utilize 10% of the GPUs potential.

In comparison, LCA is of $O(MN_\beta N_\phi)$, and extremely well suited for GPUs. Each pixel depends on only a small subset of data, and the windows can be precomputed and stored in GPU cache for near immediate access. If we use a trigonometric window function we solve for the window parameter analytically as described in appendix A. This reduces the complexity to $O(MN_\phi)$, and the only remaining LCA parameter is the steering amount.

VI. CONCLUSION

LCA seeks to improve image resolution and contrast by minimizing the power of noise and interference in each image pixel. This is the same optimization criterion as MVDR uses, but instead of computing an optimal array window like MVDR does, it selects the best window out of a predefined set. Hence, it can be viewed as either a reduced and discrete window space version of MVDR, or as an advanced multi-apodization technique. What we have studied in this paper is which windows we should ideally let LCA choose from.

We have found the LCA to be surprisingly insensitive to the exact window function it is used with, supported by the observation that near identical images were produced whether we used Kaiser or trigonometric windows. However, it needs to be able to select between wide and narrow window responses, since the wide ones offer the best sidelobe suppression and the narrow ones offer the best sensitivity. We achieved good results using 2-3 Kaiser windows in the range $\beta \in [0, 5]$, and observed minimal difference when adding more windows or adjusting the upper bound of β . For the steering angle we suggest a value in the range $\phi \in [0, \pm\delta\phi_{3dB}(\beta)]$, where $\phi_{3dB}(\beta)$ is the bandwidth of the respective window, and δ is a scaling parameters. Setting δ to either 50% or 100% reduces point target size to 73% or 53% compared to the rectangular window, respectively. Hence, it can be used to control aggressiveness and resolution gain of LCA.

In summary, LCA is an attractive alternative to other adaptive beamformers due being very fast, simple to understand, practically parameter-free, inherently robust, and able produce images similar to that of MVDR. Contrary to MVDR it has a low computational complexity, and is very well suited to be accelerated using GPUs. Since LCA performs just as well if we used trigonometric windows instead of Kaiser, we can even compute the optimal window parameter analytically for any given steering angle, and avoid the search over the window parameter entirely.

Don't think you need that comma

APPENDIX A REDUCING LCA COMPLEXITY

Throughout this article we have used LCA with the Kaiser window function. However, as shown in Fig. 7 we can obtain similar performance using the trigonometric window function. For this window we can obtain an analytic solution for the

And.....more impressive math :p

optimal value of α in the minimum variance sense. To derive it, we start by inserting the trigonometric function (13), with applied steering (11), into the beamformer equation (1):

$$\begin{aligned} \mathbf{w}^H \mathbf{x} &= \sum_{m=0}^{M-1} [\mathbf{a}_\phi]_m \left(\alpha - (1-\alpha) \cos \left(\frac{2\pi m}{M-1} \right) \right) x_m^* \\ &= \alpha \mathbf{a}_\phi^T \mathbf{x} - (1-\alpha) \mathbf{b}_\phi^T \mathbf{x} \end{aligned} \quad (15)$$

where $[\mathbf{a}_\phi]_m$ is the m th component of the steering vector \mathbf{a}_ϕ defined in (11), and

$$\mathbf{b}_\phi = \text{diag}(\mathbf{a}_\phi) \cdot \begin{bmatrix} 1 & \cos \left(\frac{2\pi}{M-1} \right) & \cos \left(\frac{2\pi 2}{M-1} \right) & \dots & 1 \end{bmatrix}^T. \quad (16)$$

Unity gain in the look direction is ensured as long as the weights sum to one:

$$\mathbf{w}^T \mathbf{1} = (\alpha \mathbf{a}_\phi - (1-\alpha) \mathbf{b}_\phi)^T \mathbf{1} = 1. \quad (17)$$

This is true for any value of α if $\mathbf{a}_\phi^T \mathbf{1} = 1$ and $\mathbf{b}_\phi^T \mathbf{1} = 1$. Hence, we preserve the unity gain constraint as long as we normalize \mathbf{a}_ϕ and \mathbf{b}_ϕ .

Now let $a = \mathbf{a}_\phi^T \mathbf{x}$ and $b = \mathbf{b}_\phi^T \mathbf{x}$. The beamformer output can then be written as:

$$\begin{aligned} |\mathbf{w}^H \mathbf{x}|^2 &= |\alpha a - (1-\alpha)b|^2 \\ &= \alpha^2(aa^* + ab^* + a^*b + bb^*) \\ &\quad - \alpha(ab^* + a^*b + 2bb^*) + bb^* \end{aligned} \quad (18)$$

This is a convex function with a single minimum, which we find by differentiating with respect to α and setting equal to 0:

$$\begin{aligned} \frac{\partial}{\partial \alpha} |\mathbf{w}^H \mathbf{x}|^2 &= 2\alpha(aa^* + ab^* + a^*b + bb^*) \\ &\quad - (ab^* + a^*b + 2bb^*) = 0, \end{aligned} \quad (19)$$

which has the solution:

$$\alpha = \frac{ab^* + a^*b + 2bb^*}{2(aa^* + ab^* + a^*b + bb^*)}. \quad (20)$$

In this computation there are only 4 and 7 unique complex additions and multiplications, respectively. If we used this to analytically solve for α , but perform the search for ϕ , the computational complexity of LCA would be of $O(MN_\phi)$ instead of $O(MN_\alpha N_\phi)$. The solution for α would also yield the optimal beamformer output in the minimum variance sense.

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Joey :) You really are brilliant! Amazing paper! I knew you could do it!

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