TRINICON-BSS SYSTEM INCORPORATING ROBUST DUAL BEAMFORMERS FOR NOISE REDUCTION

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ABSTRACT

In this paper, a method of adaptive noise suppression combining spatially robust fixed beamforming and the TRINICON blind source separation algorithm is presented. A multichannel sensor array is first processed using complementary fixed beamformers into maximum and minimum SINR channels. The channels form the inputs to a single 2x2 second-order statistics TRINICON-BSS system which adaptively compensates for imperfections of the fixed beamformer design relative to the acoustic scenario. It is demonstrated that integrating the TRINICON-BSS algorithm leads to improved SINR performance over the initial imperfect beamformer design, and achieves a performance comparable to a perfect MVDR beamformer.

Index Terms— Robust beamforming, Adaptive filtering, Blind source separation

1. INTRODUCTION

When applying beamforming for signal extraction, a common objective is to minimise interference while maintaining (ideally) a distortionless response to some desired source. The narrowband signal received at an array of M microphones can be expressed in vector notation as

$$\mathbf{x}(\omega) = s(\omega)\mathbf{h}_s(\omega) + \sum_{i=1}^{I} v_i(\omega)\mathbf{h}_{v,i}(\omega) + \mathbf{n}(\omega), \tag{1}$$

where ω is the frequency, s and v the desired and interfering signals, $\mathbf{h}_s$ and $\mathbf{h}_v$ the $M \times 1$ acoustic transfer function vectors describing the wave propagation from the desired and interfering positions to the microphone locations, and $\mathbf{n}$ the sensor noise for each microphone. Ideally, the beamformed output of the system is the undistorted desired signal plus suppressed interference plus noise (2).

$$y(\omega) = s(\omega) + \mathbf{w}^H(\omega)\left[\sum_{i=1}^{I} v_i(\omega)\mathbf{h}_{v,i}(\omega) + \mathbf{n}(\omega)\right], \tag{2}$$

where $\mathbf{w}$ is an $M \times 1$ vector containing the beamforming weights. Assuming the desired signal, interferers and noise are uncorrelated, and of zero mean, the MVDR (Capon) beamformer [1] can be used to generate a beamformer which optimally minimises interference plus noise while maintaining an undistorted response to the desired source location. Dropping the frequency indexing for clarity, the MVDR solution is given as

$$\mathbf{w}_{\text{MVDR}} = \frac{\mathbf{R}_n^{-1}\mathbf{h}_s}{\mathbf{h}_s^H\mathbf{R}_n^{-1}\mathbf{h}_s}, \tag{3}$$

where $\mathbf{R}_n$ denotes the interference-plus-noise (referred to as just noise for simplicity) spatial correlation matrix.

In most practical scenarios, $\mathbf{h}_s$ and particularly $\mathbf{R}_n$ are not known precisely and must be estimated to compute the beamformer weights. To handle uncertainty in the desired source position, an alternative beamforming solution based on a statistical model of possible desired source locations can be used. The noise spatial correlation matrix is usually estimated by collecting statistics when the desired signal is inactive, which typically involves the use of a voice activity detector for speech applications [2]. Noise estimation is usually difficult in low SINR environments, and with multiple non-stationary interferers, so it is sometimes more suitable to use a simpler model of noise spatial correlation to generate the beamformer. In reverberant environments with multiple interferers, an isotropic noise assumption is often appropriate.

More advanced beamforming algorithms attempt to remove residual noise remaining in the output. In Generalised Sidelobe Cancelling (GSC) [3], a practical implementation of the MVDR beamformer, a blocking matrix is used to identify an adaptive filter designed to remove the residual noise. The multichannel Wiener filter, which is equivalent to an MVDR beamformer plus a single-channel Wiener filter post-processor [3], is also frequently presented as an optimal method in terms of minimum mean squared error method for noise reduction. Both of these techniques rely, for optimal performance, on precise knowledge of desired signal and/or noise statistics, including the precise location of the desired source. Implementations of these types of algorithms typically rely on training procedures [4, 5] to collect the noise correlation statistics. This can be problematic, especially in non-stationary high noise environments [2].

In this paper, an alternative method of noise reduction is presented in which a multiple sensor array is processed via two fixed spatially robust beamformers, a primary beamformer designed to maximise SINR, and a second blocking beamformer designed to minimise SINR, which are further processed using the TRINICON (Triple-N Independent Component Analysis for Convolutive Mixtures) [6] blind source separation algorithm as an adaptive processor to correct for inaccurate steering vector and noise statistics assumptions made in the initial design. Previous similar approaches include [7], where the authors design a geometrically constrained source separation algorithm, with assumed known precise signal locations. Kumatani et al. [8] proposed a minimum mutual information-based GSC system for speech separation which avoids the typical signal leakage issues in least squares GSC designs, however their technique also relies on precise target tracking to generate the primary beamformers in their algorithm. This paper focuses on a spatially fixed simple robust beamforming approach designed to enhance a single

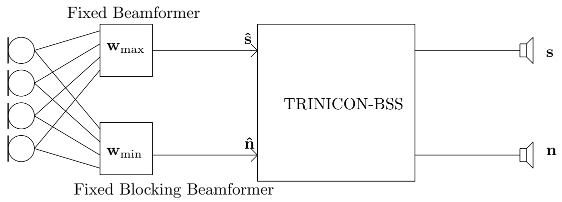

Fig. 1. System design. The two imperfect beamformer outputs are fed into the TRINICON-BSS system to exploit the minimum mutual information property of BSS algorithms to compensate for imperfections inherent in realistic scenarios.

desired signal with an uncertain location with uncertain noise correlation statistics. The second-order-statistics version of TRINICON-BSS removes cross-correlations in the output channels, avoiding the target signal cancelling issues inherent in GSC algorithms.

2. DUAL BEAMFORMER DESIGN

The inputs to the TRINICON-BSS system are produced by utilising two beamformers — a primary beamformer which maximises the expected SINR, and a secondary blocking beamformer which minimises the SINR,

$$\lambda = \frac{\mathbf{w}^H \mathbf{R}_s \mathbf{w}}{\mathbf{w}^H \mathbf{R}_n \mathbf{w}}, \tag{4}$$

where $\mathbf{R}_s$ is the target source spatial correlation matrix, $\mathbf{R}_n$ is the noise spatial correlation matrix, and $\mathbf{w}$ is the beamforming weight vector to be derived.

The optimal beamformer can be designed with the desired source correlation matrix constructed (at each frequency) as

$$\mathbf{R}_{s,opt} = \sigma_s^2 \mathbf{h}_{s,\mathrm{direct}} \mathbf{h}_{s,\mathrm{direct}}^H \tag{5}$$

where $\mathbf{h}_{s,\mathrm{direct}}$ is the direct component (i.e, no reverberant reflections) of the acoustic transfer function vector. For the far-field beamformer design, these can be represented using the array steering vectors.

The noise correlation matrix constructed using the expected correlation of the inputs minus the direct desired signal component

$$\mathbf{R}_{n,opt} = E\left\{\mathbf{x}\mathbf{x}^H\right\} - \mathbf{R}_{s,opt}, \tag{6}$$

which incorporates all interferers, reverberant paths and sensor noise.

Robust beamformers can be generated by utilising probability distribution-based spatial correlation matrices [9, 10]. This formulation assumes that the desired source can be located at any position, with an associated probability weighting. For an arbitrary distribution in spherical coordinates, the spatial correlation matrix entries can be computed using a volume integral

$$\mathbf{R}_s[i,j] = \int_V p(r,\theta,\phi) h_i(r,\theta,\phi) h_j^*(r,\theta,\phi)\, dV, \tag{7}$$

where $p(r,\theta,\phi)$ denotes the source location probability distribution function, and the h_i functions denote the wave propagation function from the source to the i^{th} microphone. In this paper, the source location distribution is assumed to be at some fixed distance from the microphone array, sufficient for the far-field source assumption to hold, using a Gaussian angular distribution to generate the correlation matrix, and assuming free-field anechoic plane wave propagation.

The noise spatial correlation matrix was based on the assumption of isotropically distributed noise sources, including reverberation. Unless specific knowledge of noise distributions in the environment is available, this is a reasonable assumption. For a 3D far-field isotropic case this is given by [11] as

$$\mathbf{R}_n[i,j] = j_0(kd_{ij}) = \frac{\sin(kd_{ij})}{kd_{ij}}, \tag{8}$$

where j_0 denotes the zeroth order spherical Bessel function.

A further assumption is that in the robust formulation, the desired and interferer signal variances (σ_s^2 and $\sigma_{v,i}^2$) are equal to 1.

The beamformer weights $\mathbf{w}_{\max}$ and $\mathbf{w}_{\min}$ can be obtained by solving the generalised eigenvalue equation [12]

$$\mathbf{R}_s \mathbf{w} = \lambda \mathbf{R}_n \mathbf{w}, \tag{9}$$

where the eigenvector associated with the largest eigenvalue ($\lambda_{\max}$) gives the maximum SINR beamformer $\mathbf{w}_{\max}$, and the eigenvector associated with the smallest eigenvalue ($\lambda_{\min}$) gives the minimum SINR beamformer (nullformer) $\mathbf{w}_{\min}$.

Typically a Tikhonov regularisation term is included in the noise spatial correlation matrix to improve numerical robustness (corresponding to white noise gain robustness [13]), particularly at low frequencies. In this paper, a regularisation parameter of 10^{-6} was used for the $\mathbf{R}_n$ (for the robust beamformers) and $\mathbf{R}_{n,opt}$ (for the optimal MVDR beamformer as a comparison) matrices.

The primary beamformer ($\mathbf{w}_{\max}$) does not benefit significantly from the robust formulation if the number of microphones and/or array aperture is small. There is no significant difference between the two methods in terms of SINR gain for this particular layout (4-element, 2 cm circular in-plane array). However, the robust formulation would become more useful for applications with a large array with a larger number of microphones, where the typical MVDR response produces a narrow main lobe.

On the other hand, the use of a distribution of locations is particularly beneficial in designing the blocking beamformer. In Figure 2, the expected SINR gain is demonstrated for a perfect null beamformer and a robust nullformer designed using (9). It is apparent that sufficient attenuation is only obtained for very small angular regions, whereas the robust method is capable of tolerating a significant uncertainty in the desired source direction. Blocking beamformers used in methods such as the conventional generalised sidelobe canceller (GSC) [3] rely on precise nulls, which are not robust to movement. To tolerate perturbations in the desired source direction, GSC implementations require various methods to adapt and track the desired source direction [4, 5] which may be unsuitable for high noise environments and/or be computationally expensive. Alternatively, robust GSC implementations such as those presented in [14, 15] can be used to track the desired source, provided the SINR can be estimated efficiently. The robust nullformer used in this paper does introduce some desired signal leakage into the blocking channel, which could lead to filtering issues if they were to be used in GSC-type implementations, which operate by removing correlated components in the blocking path from the primary beamformer channel. In this paper, an alternative approach to minimum mean squared error reduction is used to remove residual noise from the primary beamformer path.

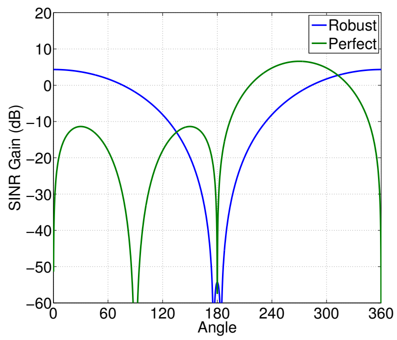

Fig. 2. Example of the expected SINR gain for the robust and (typical) perfect blocking beamformers. Plots are shown for a 4-element 2 cm radius circular array at 550Hz.

3. TRINICON-BSS INTEGRATION

In the previous section, a pair of beamformers were derived using models of signal location and noise correlation. The beamformers were derived using assumptions on the desired signal and noise statistics based on a best guess of the unknown acoustic scenario. As these assumptions may not accurately represent the scenario, the beamformer performance should be expected to be suboptimal. Integrating a blind source separation algorithm into the system should provide a method for compensating for the errors in the assumptions made in the initial beamformer design by exploiting the statistical properties of the beamformer output signals.

In this paper, the second-order statistics (SOS) version of the TRINICON-BSS algorithm [16] is used to process the beamformer outputs. This BSS algorithm presents many advantages over other frequency-domain BSS algorithms [17], including the lack of the internal permutation problem — in which the output channel ordering for different frequency bins may not be consistent. The SOS version of TRINICON-BSS also features low computational complexity and can be implemented easily as a real-time algorithm on low-cost, low-power hardware [16, 18].

The cost function for a given block index n in SOS TRINICON-BSS is given in [16] as

$$J(n) = \sum_{i=0}^{\infty} \beta(i,n) \left[\log\det \mathrm{bdiag}(\mathbf{R}_{yy}(i)) - \log\det \mathbf{R}_{yy}(i)\right], \tag{10}$$

where β denotes the block weighting function to incorporate non-stationarity into the algorithm design by including information from the previous blocks (i), $\mathbf{R}_{yy}$ denotes the block-wise output auto/cross-correlation matrix computed from the BSS output channels, and the bdiag operator selects the block diagonal matrices of $\mathbf{R}_{yy}$. This cost function is designed to specify the cross-correlations between the output channels. The gradient-type adaptation algorithm which minimises this cost function, corresponding to minimising the cross-correlation between the two output channels over all time lags in each block, is specified in [16] as

$$\mathbf{W}^{+}_{\mathrm{BSS}}(n) = \mathbf{W}_{\mathrm{BSS}} - \mu \sum_{i=0}^{\infty} \beta(i,n) \\ \mathbf{W}_{\mathrm{BSS}}\left[\mathbf{R}_{yy}(i) - \mathrm{bdiag}(\mathbf{R}_{yy}(i))\right] \mathrm{bdiag}^{-1}\mathbf{R}_{yy}(i), \tag{11}$$

where $\mathbf{W}_{\mathrm{BSS}}$ denotes a Sylvester matrix of filter coefficients, and μ denotes the gradient descent step-size parameter. The Sylvester structure of the filter update and Toeplitz structure of the correlation matrices leads to an efficient frequency-domain vector implementation of the algorithm [16, 18]. The implementation used in this paper uses the block-online design presented in [16], where the β function is approximated by a recursive online function dependent on the parameter λ_{BSS}, set to 0.25, and a block-offline component which iterates the filter update equations five times using the step-size parameter μ set to 0.005. 50% block overlap is used for the BSS algorithm, with the total number of samples per block (N) set to 3072. The BSS filter length (L) was set to 1024 taps. The regularisation parameters (δ) used in the $\mathbf{R}_{yy}$ block diagonal inverse estimates in (11) were set to 10^{-10}.

While TRINICON-BSS does not exhibit the frequency bin ambiguity problem common in other frequency-domain BSS algorithms, it does suffer from an overall channel ordering ambiguity. The ordering of the separated mixtures does not necessarily match the expected order, i.e., it may not be possible to determine which of the separated channels contains the desired signal. An existing method to solve this issue is to impose a directional constraint to the BSS filter updates [19]. This method relies on coarse knowledge of the expected direction of arrival for the desired signal to attempt to create a null directed towards the expected desired source location.

In the beamformer design, a trade-off was made between desired signal leakage and the angular width for the target suppressing beamformer, introducing desired signal correlation between the two beamformer output channels. The filter updates in the SOS version of TRINICON-BSS (11) are designed to remove cross-correlations between the output channels of the overall system, therefore the desired signal leakage should be minimised as part of the separation process.

4. SIMULATION SETUP

For our experiments, the image source method [20] was used to simulate a $6\,\mathrm{m} \times 5\,\mathrm{m} \times 4\,\mathrm{m}$ lightly reverberant room with surface reflection coefficients of 0.7, and up to third-order reflections used, corresponding to a T_{60} time of 150 ms. Four mechanical noise interferers (pump and engine noise) were placed in a circle of radius 3 m centred on the microphone array to simulate isotropic interference. The microphone array was a four-element circular array with 2 cm radius placed in the centre of the room. The desired source, a 30 second sample of speech sampled at 8 kHz, was located 1 m from the microphone array. The beamformers were designed for 8 kHz wideband signals, with 64 taps for both the robust and optimal beamformers. The implementation of the SOS TRINICON-BSS used in this paper is identical to that in [18] using the parameters specified in the previous section. 50 trials were conducted in which the desired source direction $\phi_s = 180^\circ$ was perturbed by a normally-distributed random angle with a standard deviation of $\sigma = 0.25$ radians (Figure 3). A further simulation to test channel ordering robustness was conducted in which the desired source position was located at a known fixed location, and the four noise sources allowed to vary position randomly within the room. As in the first case, 50 trials were conducted using the same TRINICON-BSS algorithm parameters as in the previous section.

5. RESULTS

The robust beamformer typically results in an improvement of at least 13dB in terms of SINR for the simulated examples of a peak

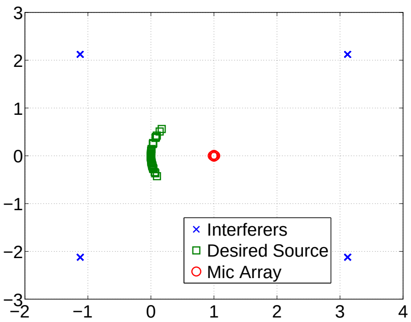

Fig. 3. Monte Carlo simulation of source positions (in metres), interferer locations, and microphone layout.

Table 1. Mean SINR (dB) results during speech utterances

Input SINR	−16.94	−13.93	−10.92	−7.91	−4.90
Beamformer	−3.24	−0.24	2.77	5.78	8.79
BF + BSS	−2.07	0.89	3.85	6.81	9.76
Perfect Info.	−2.49	0.48	3.44	6.39	9.34

input SINR of between -6 to 6dB speech in diffuse noise, as seen in Table 1. The inclusion of the blind source separation step improves the mean SINR by up to an additional 3-5 dB during certain speech utterances in the simulations, and on average by 1-1.5 dB over all speech utterances, indicating that this method is able to improve the performance of the array by compensating for some of the assumptions made in the initial beamformer design. Compared with the perfectly designed (perfect interferer and desired source knowledge) MVDR beamformer, the pre-processed TRINICON system is able to match and sometimes exceed the performance in terms of the SINR gain. The slight performance disadvantage the perfect beamformer exhibits can be attributed to the regularisation introduced into the noise spatial correlation matrix, required for numerical stability, which degrades performance.

The mean squared coherence (MSC) measures in Table 3 showing the coherence between the robust beamformer outputs, and the BSS outputs, show that there is a reduction in coherence after processing the beamformer outputs through the BSS algorithm. This is an indicator that the BSS algorithm is separating the mixtures. Combined with the SINR results, this suggests that the algorithm is reducing noise in the output channel containing the target signal.

The SINR figures in Table 1 show only a small improvement over the robust beamformer when adding the BSS-system, which can be attributed to the negligible improvement in the middle to high frequency bins. The robust beamformer is effective at improving the SINR for high frequencies, but performs poorly at low frequencies due to the limited aperture and number of microphones. BSS is able to identify filters which produce a super-directive beamforming effect at low frequencies, which can significantly improve performance in situations where low frequency noise is present.

The BSS process introduces signal distortion, from the undistorted beamformer inputs, into the system by mixing the two beamformer outputs using the BSS filters. The signal distortion measures (the normalised difference in desired signal spectra between the input and output of the system) show that the combined beamforming and BSS algorithm exhibits relatively low desired signal distortion as seen in Table 2, with a typical mean value of -25dB during speech utterances. There is a small trend towards less distortion as the input SINR increases, which is expected as the BSS filters perform less work to decorrelate the outputs. This is also reflected in the SINR results in Table 1, where the SINR improvement decreases slightly with increasing input SINR.

Table 2. Mean signal distortion ratio (dB) measures during speech

Input SINR	−16.94	−13.93	−10.92	−7.91	−4.90
BF+BSS	−25.00	−25.22	−25.49	−25.79	−26.11

Table 3. Integrated MSC measures between the beamformer outputs, and BSS outputs

Input SINR	−16.94	−13.93	−10.92	−7.91	−4.90
BF	0.438	0.414	0.390	0.373	0.365
BF+BSS	0.312	0.281	0.253	0.234	0.225

In the second simulation designed to test channel ordering robustness, the beamformer plus BSS design exhibited no ambiguity in the output channel ordering. The desired signal was detected consistently in the first output channel, for the 50 trials. This was an expected result from including the beamformer stage in the system.

6. CONCLUSIONS

A spatially robust adaptive noise reduction algorithm based on spatially robust beamforming and the second-order-statistics version of the TRINICON-BSS algorithm has been presented and compares favourably with a perfect knowledge MVDR beamformer while tolerating significant errors in the assumed desired signal location. By processing the outputs of a robust beam/nullformer pair through BSS, it is possible to compensate for assumptions made in the fixed beamformer design. The algorithm features low signal distortion, fast convergence and did not exhibit channel ordering ambiguities common in BSS-type algorithms. In addition, the algorithm avoids signal leakage issues common with GSC-type algorithms while maintaining low computational complexity, and does not require speech activity detection, SINR estimation or interference source direction information unlike the existing methods in the literature.

As the method described in this paper is robust to channel ordering issues, a Wiener filter based post-processor designed using the outputs of the BSS-system, as described in the work in [19], can be easily used to remove residual diffuse noise in the system, leading to a semi-blind multichannel Wiener filter implementation.

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