

Gain Enhancement of Acoustic Beamforming Arrays in Complex Dynamic Systems

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Abstract: Acoustic beamforming in complex dynamic systems is a non-trivial task given the time-variant nature of system variables. For a time-invariant system, the dynamics of the system can be modelled and utilised to estimate the system behaviour in real-time. This paper presents a regulated-element Frost (REF) beamforming algorithm for acoustic characterisation of dynamic systems in real-time. The REF beamformer is an adaptive algorithm that selectively enhances the desired signal based on the noise conditions of the individual sensors thereby avoiding noisy signal leaks through the finite impulse response (FIR) filters of each sensor. In this paper, the diffuse noise field is considered for omnidirectional sensors deployed in a dynamic automobile environment. The REF technique can be implemented in both endfire and broadside array configurations. The simulation results show that the gain enhancement of REF is better by more than 2 dB than the Frost beamforming and requires less sensors and filter taps for FPGA-based embedded real-time implementations.

Keywords: Adaptive beamforming, Automobile Infotainment, Dynamic Systems, Gain Enhancement, Regulated Sensors

1. Introduction

The dynamics of static and mobile systems have prompted more research into their deterministic characterisations using embedded systems. Acoustic beamforming algorithms have been investigated and developed for various applications including sonar and communications. The modern infotainment systems have also relied on the accurate validation of the sensor requirements for a high quality sound production. During a system implementation, fixed beamformers are insensitive to the dynamics of the environment while adaptive beamformers have their data adjusted to suit the state of the environment.

Microphone array beamforming has been investigated and utilised to extract desired audio signals in different environments characterised by interference and noise. Beamforming operations aim at enhancing the gain and quality of speech signals for detection, perception and post-processing. The noisy environment can be static or mobile. The mobile environment presents a unique system characterisation challenge in that the location and spacing of the sensors are critical for achieving the best performance in any array configurations the sensors receive the incident signal(s). Furthermore, the mobile environment can exhibit mechanical, electrical, acoustic (over-the-air), pneumatic, hydraulic and thermal noises; radio frequency and electromagnetic interferences are also possible. This calls for the design and development of a robust and reliable system-focused algorithm that performs spatial signal processing in a manner that

boosts the array gain and reduce the residual noise and interferences. Adaptive beamformers have the capability to enhance the capturing of the desired signal in a given incident direction while adjusting its directivity to reduce the interference and jammers. Adaptive beamforming schemes have been developed including least mean squares, sample matrix inversion, recursive least square, conjugate gradient and constant modulus algorithms [2–5]. An acoustic array for speech acquisition should be able to operate uniformly across a large wideband with nearfield sources; the array requires a narrow main beam in the desired target signal direction. The use of farfield assumptions to design the beamformer degrades the beampattern for nearfield sources such as microphone arrays in a car. The antenna community [5] has utilised the theory of nearfield-farfield transformation to achieve a computationally simple design procedure. The approximate distance, r , from an acoustic source to an arbitrary array origin for the farfield assumption to be valid is at $r = 2L^2/\lambda$, where L is the largest array dimension and λ , the operating wavelength. This condition has been made unnecessary by the farfield-nearfield transformations [5].

This paper is organized as follows. Section 2 explains the general concept of acoustic beamforming with a specific emphasis on dynamic systems. This section also features the key parameters of adaptive beamforming design for the mobile environment characterized by noise and interference sources. The regulated-element Frost algorithm is presented in section 3. The microphone array beamforming simulation of dynamic systems is stated in section 4. In section 5, the pertinent results and discussions are given. Section 6 concludes the paper.

2. Acoustic Beamforming in Dynamic Systems

Dynamic systems such as a shopping mall, conference auditorium, underwater operations, airport, seaport, warehouses, production yards, factories and process plants present different noise fields for sound detection and/or perception. Consequently, beamforming operations that perform signal processing deterministically have been investigated for sensor arrays including microphone arrays and sonar arrays. Microphone arrays have found tremendous applications in improving the quality of received audio signals. Uniform linear arrays of microphones have been deployed for spatial filtering targeting interference and/or noise rejection. This enhances the quality and gain of the desired signal.

Adaptive beamformers have been studied and implemented for various acoustic applications [1–5]. In spatial filtering, the desired signal from a given source(s) and direction(s) is captured using a beamformer. The beamformer applies weight vectors to enhance the desired signal and yield a unity response in the broadside or “look” direction. The noise and interference signals are weighted in such a way that the desired response is zero outside the frequency range of interest. In a dynamic system, the data is not wide-sense stationary and the second order statistics are unknown. Adaptive beamforming applies weights to the signal samples of the sensors according to the data statistics received at the uniform linear array (ULA). The output of the beamformer contains minimal components of noise and interference signals. The weight vector that yields the optimum result depends on the cross covariance between the received unknown desired signal and the reference signal utilised in the beamformer. Hence, the properties of the unknown signal are exploited to obtain the approximate adjustable weights (AWs) per sensor channel for the beamforming operation.

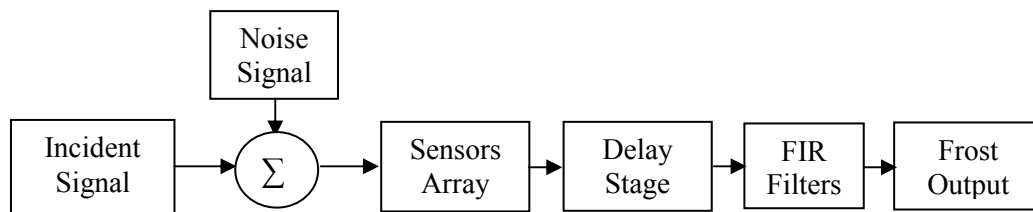


Fig. 1. The Frost Beamformer

Figure 1 shows the Frost beamformer; a hybrid of it, which offers a higher capability of jammers suppression and rate of convergence, has been proposed in [2]. These are adaptive beamforming implementations which apply linear constraints to the weight vector due to the lack of knowledge of the desired signal. The Frost beamformer uses the linearly constrained minimum variance beamforming technique to control the beamformer output adaptively. Other proposed adaptive algorithms are the generalised sidelobe canceller (GSC) and the Howells-Applebaum adaptive loop [4].

3. The Regulated-Element Frost Beamforming Algorithm

Knowing the reference signal a priori enables the appropriate choice of the sensor weights to reduce or eliminate the error and/or mismatch between the beamformer output and the desired signal. If the statistics of the incoming signal were known, there would be no need for beamforming.

The regulated-element Frost beamforming algorithm (REFBA) chooses weights to minimise the mean square error between Frost beamformer output and the reference signal based on an adaptive detection of the received signal at each sensor. The REF beamforming architecture is illustrated in Fig. 2.

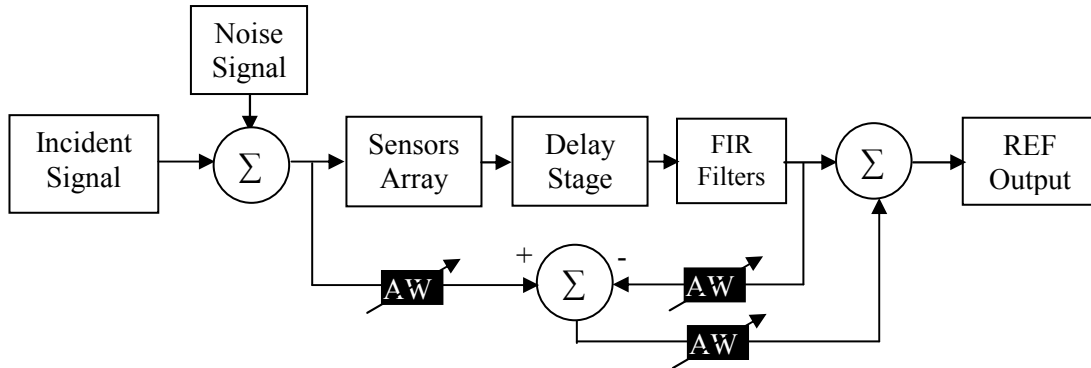


Fig. 2. The REF Beamformer

The received signal, S_r , for the entire ULA is given by:

$$S_r = \sum_{i=1}^N S'_i \quad (1)$$

where the received signal, S'_i , at each sensor is given as a function of the desired signal, S_i , and dynamic system noise, n_i , thus:

$$S'_i = S_i + n_i \quad (2)$$

and the residual noise, n'_o , is estimated thus:

$$n'_o = \frac{S_r}{N^N} - NF_o \quad (3)$$

The output of the REF algorithm is obtained by applying the weight vector to the Frost beamformer based on the incoming data statistics at each sensor. Mathematically, this is given by:

$$REF_o = F_o + \frac{S_r - NF_o}{N^N} \quad (4)$$

Hence, the REF output, REF_o , can be computed using the following relationship thus:

$$REF_o = \frac{1}{N^{2N}} \left(N^{N+1} (N^{N-1} - 1) F_o + \sum_{i=1}^N (S_i + n_i) \right) \quad (5)$$

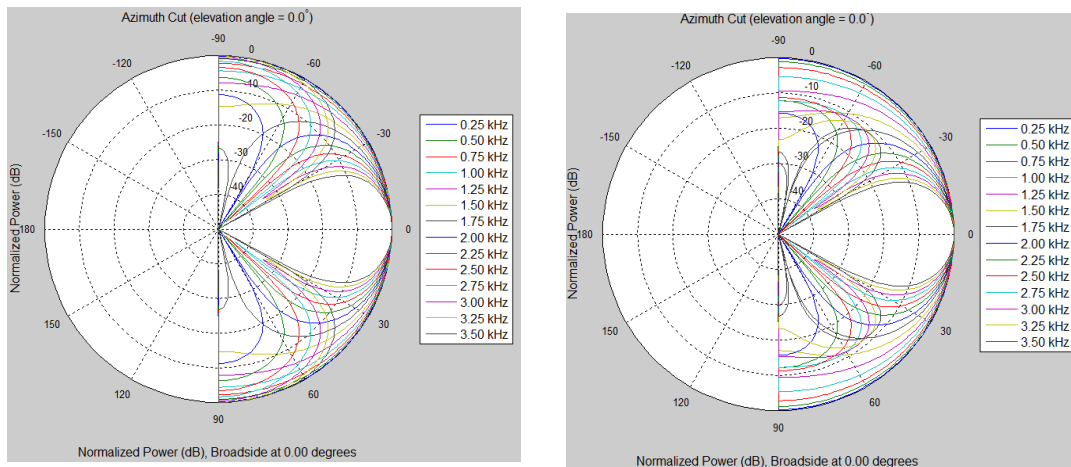
where, N represents the number of ULA sensors deployed and F_o , the output of the Frost beamformer.

4. MAB Simulations of Dynamic Systems

The microphone array beamforming (MAB) simulation of dynamic systems enables the acoustic response of such systems to be estimated for sensor design, development and deployment purposes. Amongst the key parameters of interest are the frequency range, sensor technology, spacing between the sensors and the number of sensors. For adaptive beamformers, the number of finite impulse response (FIR) filters required is also estimated. In this paper, these parameters were considered to compare the performance of the REF algorithm with the conventional Frost beamforming technique and the simulation results are given in the next section.

5. Results and Discussion

In order to understand and estimate the ULA sensors and their spatial separation, the radiation patterns of omnidirectional microphones were investigated over the frequency range of the human voice. Figure 3 shows the polar pattern for a 2- and 4-element ULA spaced at 10 cm. The frequency response shows a unity directivity at the broadside (look direction) angle of zero degree. As the number of sensors increases, the sidelobes become prominent as shown in Fig. 3; it is obvious from the plot that the directivity of the ULA also degrades across the frequency range of interest.



(a) Two sensors (b) Four sensors
Fig. 3. Radiation Pattern of an Omnidirectional ULA at a sensor spacing of 10 cm

For a 4-element ULA spaced at 10 cm, the signal attenuation can be as high as 40 dB for quite a

substantial part of the voice bandwidth. The frequency response also shows that the array directivity degradation increases as the spacing between the sensors increases. Hence, the array design must incorporate adequate signal processing routines to cater for the signal losses and leaks due to speech quality degradation issues including spatial aliasing, diffuse noise fields and interferences.

The simulation of the omnidirectional ULA was investigated using 2- and 4-element ULAs each spaced at 10 cm. A frequency domain analysis (using the fast Fourier transform (FFT)) can be carried out at the input of the ULA for the spectral analysis of the incoming signal. A corresponding time domain analysis can be implemented (using the inverse FFT) to recover the signal and play as an analogue output.

Figures 4 and 5 show the signal-to-interference-and-noise ratio (SINR) gain for the ULA system using the conventional Frost beamformer algorithm (FBA) and the developed REFBA. It is obvious that the REFBA outperforms the FBA by over 2 dB gain; the lowest REFBA gain is 7 dB and FBA, 1 dB. Similarly the SNR-based steering gain (Figs. 6) for the REFBA ULA reveals a gain enhancement of over 5 dB more than the FBA output in the incident angle $(-30, 0)$ direction. The SNR-based ULA system selectivity (Figs. 7 and 8) for the REFBA yields approximately 5 dB gain more than the FBA response. The results indicate that fewer filter taps for the REFBA than for the FBA; in the former, the performance improvement is impressive with a lower computational cost than the latter. Since one needs to invert a 4-by-2 matrix, the REFBA offers a less expensive real-time processing using a field programmable gates array (FPGA)-based embedded signal conditioning system.

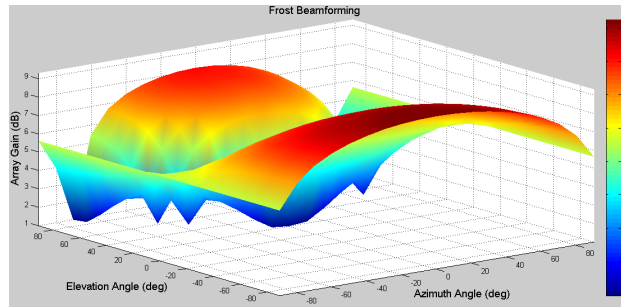


Fig. 4. SINR-based ULA Gain for the FBA ($N = 2$; $d = 10$ cm; Filter Length = 5)

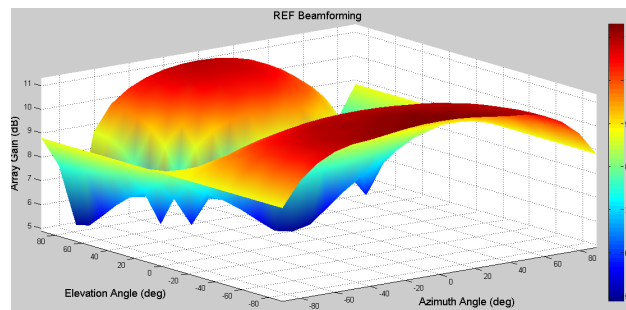


Fig. 5. SINR-based ULA Gain for the REFBA ($N = 2$; $d = 10$ cm; Filter Length = 5)

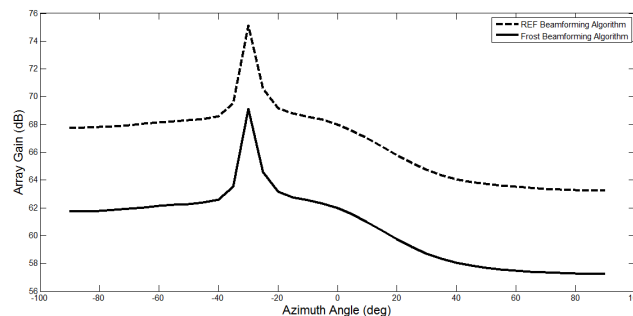


Fig. 6. SNR-based Steering Gain for the FBA and REFBA ($N = 2$; $d = 10$ cm; Filter Length = 2)

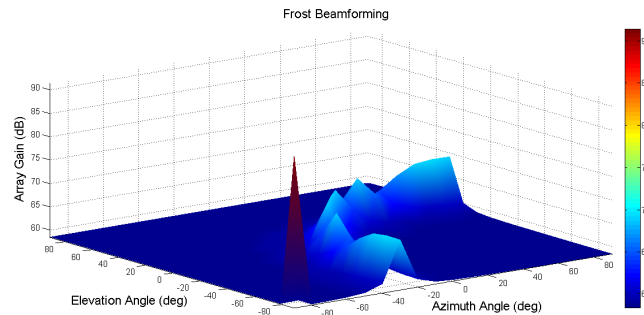


Fig. 7. SNR-based System Selectivity Gain for the FBA ($N = 2$; $d = 10$ cm; Filter Length = 4)

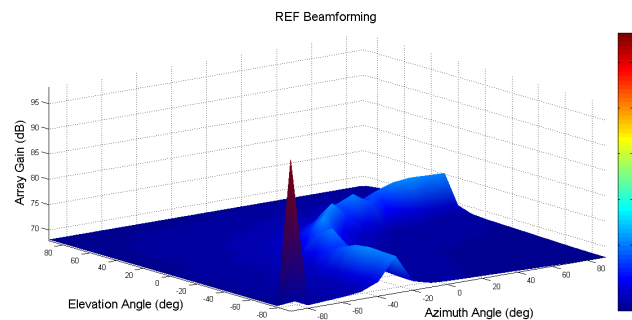


Fig. 8. SNR-based System Selectivity Gain for the REFBA ($N = 2$; $d = 10$ cm; Filter Length = 2)

6. Conclusions

This paper has presented a novel adaptive beamforming algorithm for enhancing the speech quality within dynamic mobile systems that deploy acoustic sensors and/or transducers. The investigation focused on omnidirectional microphones with finite impulse response filters placed at each sensor to offer a data-dependent signal processing based on a regulated noise input across a uniform linear array. The reported regulated-element Frost beamforming technique outperforms the conventional Frost beamformer in desired signal gain enhancement, noise cancellation and interference rejection. The REF beamforming algorithm requires less sensors and FIR filters and supports close proximity placement of the array elements; its lowest SNR-based system selectivity gain is 10 dB higher than the Frost beamforming technique's lowest value. This holds a great promise for designing, developing and deploying a reliable, sustainable, cost-effective, compact and high fidelity acoustic sensor system for mobile engineering systems and applications such as next-generation automobile infotainment. The theory of REF algorithm can be extended to other areas of array processing including adaptive phased array antenna applications.

References

- [1] M. Štrupl, and P. Sovka, "Analysis and Simulation of Frost's Beamformer," *Radioengineering*, vol. 12, no. 2, pp. 1–9, 2003.
- [2] S. Chern, and C. Sung, "The Hybrid Beamforming Algorithm for Multiple Jammers Suppression," *Signal Processing*, vol. 43, pp. 113–127, 1995.
- [3] H. Hung, S. Chang, S. Chen, and C. Chang, "Real-time Implementation of Frost Beamformer for Underwater Communications," *Journal of Marine Science and Technology*, vol. 7, no. 1, pp. 1–7, 1999.
- [4] B. Veen, and K. Buckley, *Beamforming Techniques for Spatial Filtering*, CRC Press, 1999.
- [5] T. Abhayapala, and R. Kennedy, "Nearfield broadband array design using a radially invariant modal expansion," *J. Acoust. Soc. Am.*, vol. 107, no. 1, pp. 392–403, 2000.