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Progress in the implementation of state-of-the-art signal-processing schemes in sonar systems is limited mainly by the moderate advancements made in sonar computing architectures and the lack of operational evaluation of the advanced processing schemes. Until recently, matrix-based processing techniques, such as adaptive and synthetic-aperture processing, could not be efficiently implemented in the current type of sonar systems, even though it is widely believed that they have advantages that can address the requirements associated with the difficult operational problems that next-generation sonars will have to solve. Interestingly, adaptive and synthetic-aperture techniques may be viewed by other disciplines as conventional schemes. For the sonar technology discipline, however, they are considered as advanced schemes because of the very limited progress that has been made in their implementation in sonar systems.

This paper is intended to address issues of implementation of advanced processing schemes in sonar systems and also to serve as a brief overview to the principles and applications of advanced sonar signal processing. The main development reported in this paper deals with the definition of a generic beam-forming structure that allows the implementation of nonconventional signal-processing techniques in integrated active–passive sonar systems. These schemes are adaptive and synthetic-aperture beam formers that have been shown experimentally to provide improvements in array gain for signals embedded in partially correlated noise fields. Using target tracking and localization results as performance criteria, the impact and merits of these techniques are contrasted with those obtained using the conventional beam former.

Keywords—Acoustic scattering, adaptive signal processing, beam steering, beams, covariance matrices, delay estimation, digital signal processors, estimation, FIR digital filters, Fourier transforms, frequency domain analysis, frequency estimation, maximum likelihood estimation, multisensor systems, signal detection, sonar signal processing, sonar tracking, spectral analysis, synthetic-aperture sonar, underwater acoustic arrays.

NOMENCLATURE

\( ()^* \) Complex conjugate transpose operator.
\( A_s(f_t) \) Power spectral density of signal \( s(t) \).
\( AG \) Array gain.
\( \alpha \) Small positive number designed to maintain stability in normalized least mean square adaptive algorithm.
\( B(f, \theta_s) \) Narrow-band beam-power pattern of a line array expressed by \( B(f, \theta_s) = b(f, \theta_s)b^*(f, \theta_s) \).
\( B(\theta) \) Broad-band beam-power pattern of a line array steered at direction \( \theta \).
\( b(f, \theta_s) \) Beams for conventional or adaptive beam formers or plane wave response of a line array steered at direction \( \theta_s \) and expressed by \( b(f, \theta_s) = \sum_{n=1}^{N} X_n(f)d_n(f, \theta_s) \).
\( BW \) Signal bandwidth.
\( C \) Signal blocking matrix in generalized side-lobe canceller adaptive algorithm.
\( c \) Speed of sound in the underwater sea environment.
\( CFAR \) Constant false alarm rate.
\( D(f_i, \theta) \) Steering vector having its \( \eta \)th phase term for the plane wave arrival with angle \( \theta \) being expressed by \( d_{\eta}(f_i, \theta) = \exp\{j2\pi[(i-1)f_s/M]f_n(\theta)\} \).
\( d \) Detection index of receiver operating characteristic curve.
\( \delta \) Sensor spacing for a line array receiver.
\( DT \) Detection threshold.
\( E\{\cdots\} \) Expectation operator.
\( ETAM \) Extended towed array measurements.
\( \varepsilon \) Noise vector component with \( \eta \)th element \( \varepsilon_n(t_i) \) for sensor outputs (i.e., \( \varepsilon = \mathbf{\varepsilon} + \varepsilon \)).
I. INTRODUCTION

Several review articles [1]–[4] on sonar system technology have provided a detailed description of the mainstream sonar signal-processing functions along with the associated implementation considerations. This paper attempts to extend the scope of these articles by introducing an implementation effort of nonmainstream processing schemes in real-time sonar systems. The organization of this paper is as follows.

The first section provides a historical overview of sonar systems and introduces the concept of the signal-processor unit and its general capabilities. This section also outlines the practical importance of the topics to be discussed in subsequent sections, defines the sonar problem, and provides an introduction into the organization of the paper.

In Section II, we discuss very briefly a few issues of space-time signal processing related to detection and procedures for estimating sources’ parameters. Section III
deals with optimum estimators for sonar signal processing. It introduces various nonconventional processing schemes (adaptive and synthetic-aperture beam formers) and the practical issues associated with the implementation of these advanced processing schemes in sonar systems. Our intent here is not to be exhaustive but only to be illustrative of how the receiving array, the underwater medium, and the subsequent signal processing influence the performance of a sonar system. Issues of practical importance, related to system-oriented applications, are also addressed, and generic approaches are suggested that could be considered for the development of next-generation sonar signal-processing concepts. These generic approaches are then applied to the central problem that the sonar systems deal with, that is, detection and estimation.

Section IV introduces the development of a realizable generic processing scheme that allows the implementation and testing of nonlinear processing techniques in a wide spectrum of real-time sonar systems. The computing architecture requirements for future sonar systems are addressed in the same section. It identifies the matrix operations associated with high-resolution and adaptive signal processing and discusses their numerical stability and implementation requirements. The mapping onto sonar signal processors of matrix operations includes specific topics such as QR decomposition, Cholesky factorization, and singular-value decomposition for solving least-squares and eigensystem problems. Schematic diagrams illustrate also the mapping of the signal-processing flow for the advanced beam formers in sonar computing architectures.

Last, a concept demonstration of the above developments is presented in Section V, which provides real data outputs from an advanced beam-forming structure incorporating adaptive and synthetic-aperture beam formers.

A. Overview of a Sonar System

To provide a context for the material contained in this paper, it would seem appropriate to review briefly the basic requirements of a high-performance sonar system. A sonar (sound, navigation, and ranging) system is defined as a “method or equipment for determining by underwater sound the presence, location, or nature of objects in the sea” [5]. This is equivalent to detection, localization, and classification.

Fig. 1 shows one possible high-level view of a generic sonar system. It consists of a wet end, a high-speed signal processor to provide mainstream signal processing for detection and initial parameter estimation, a data manager, which supports the data and information processing functionality of the system, and a display subsystem through which the system operator can interact with the manager to make the most effective use of the information available at his command. underwater acoustic signal. These devices are hydrophone arrays having cylindrical, spherical, plane, or line geometric configurations that are housed inside domes of naval ships or towed at a depth behind a vessel. Quantitative estimates of the various benefits that result from the deployment of arrays of hydrophones are obtained by the array gain term, which will be the subject of our discussion in Section III. Hydrophone array design concepts, however, are beyond the scope of this paper, and readers interested in sonar transducers can refer to other publications on the topic [6], [7].

The signal processor is probably the single most important component in the dry end of a sonar system. To satisfy the basic requirements, the processor normally incorporates three fundamental operations: beam forming, matched filtering, and data normalization. The first two processes are used to improve both the signal-to-noise ratio (SNR) and parameter estimation capability through spatial and temporal processing techniques.

Data normalization is required to map the resulting data into the dynamic range of the display devices in a manner that provides a CFAR capability across the analysis cells. In what follows, each subsystem, shown in Fig. 1, is examined very briefly by associating the evolution of its functionality and characteristics with the corresponding technological developments.

B. Signal Processor

The implementation of signal-processing concepts in sonar systems is heavily dependent on the sonar-computing architecture characteristics, and therefore it is limited by the progress made in computing architectures. While the mathematical foundations of the signal-processing algorithms have been known for many years, it was the introduction of the microprocessor and high-speed multiplier-accumulator devices in the early 1970’s, which heralded the turning point in the development of digital sonars. The first systems were primarily fixed-point machines with limited dynamic range and hence were constrained to use conventional
beam-forming and filtering techniques [1], [3], [8]. As floating-point central processing units (CPU’s) and supporting memory devices were introduced in the mid- to late 1970’s, multiprocessor digital sonar computing architectures and modern signal-processing algorithms could be considered for implementation in real-time systems. This major breakthrough expanded in the 1980’s into massively parallel architectures supporting multisensor requirements.

Recently, new scalable computing architectures, which support both scalar and vector operations satisfying high input/output bandwidth requirements of large multisensor systems, are becoming available [9]. Announced very recently was the successful development of superscalar and massively parallel signal-processing computers that have throughput capabilities of hundred of billions of floating-point operations per second [10]. This resulted in a resurgence of interest in algorithm development of new covariance-based, high-resolution, adaptive [11]–[13] and synthetic-aperture beam-forming algorithms [14]–[20] and time-frequency analysis techniques [21].

In many cases, these new algorithms trade robustness for improved performance [11], [12], [22], [23]. Furthermore, the improvements achieved are generally not uniform across all signal and noise environments and operational scenarios. The challenge is to develop a concept that allows an appropriate mixture of these algorithms to be implemented in practical sonars [22], [23]. The advent of new adaptive processing techniques is only the first step in the utilization of a priori information as well as more detailed environmental information. Of particular interest is the rapidly growing field of matched field processing (MFP) [24], [25]. The use of linear models will also be challenged by techniques that utilize higher order statistics [21], neural networks [26], fuzzy systems [27], chaos, and other nonlinear approaches. These concerns have been discussed very recently [9] in a special issue of the IEEE JOURNAL OF OCEANIC ENGINEERING devoted to sonar system technology. A detailed examination of MFP can be found also in the July 1993 issue of the above journal, which was devoted to detection and estimation in MFP [25].

C. Data Manager and Display Subsystem

Processed acoustic data at the output of the mainstream signal-processing system must be stored in a temporary data base before it is presented to the sonar operator for analysis. Until very recently, owing to the physical size and cost associated with constructing large acoustic data bases, the data manager played a relatively small role in the overall capability of the sonar system. However, with the dramatic drop in the cost of solid-state memories and the introduction of more powerful microprocessors in the 1980’s, the role of the data manager has now been expanded to incorporate localization, tracking, and classification functionality in addition to its traditional display data management functions.

Normally, the processing and integration of information from sensor level to a command and control level includes a few distinct processing steps. Fig. 2 shows a simplified overview of the integration of four different levels of information for a sonar system. These levels consist mainly of:

- navigation and nonacoustic data from receiving sensor arrays;
- environmental information and estimation of propagation characteristics in order to assess the medium’s influence on sonar system performance;
- signal processing of received acoustic signals that provides parameter estimation in terms of bearing, range, and temporal spectral estimates for detected signals;
- signal following (tracking) and localization that monitors the time evolution of a detected signal’s estimated parameters.

This last tracking and localization capability allows the sonar operator rapidly to assess the data from a multisensor system and carry out the processing required to develop an acoustically based tactical picture for integration into the platform-level command and control system.

To allow the data bases to be searched effectively, a high-performance OMI is required. These interfaces are beginning to draw heavily on modern workstation technology through the use of windows, on-screen menus, etc. Large flat-panel displays driven by graphic engines, which are equally adept at pixel manipulation as they are with three-dimensional object manipulation, will be critical components in future systems. It should be evident by now that the term “data manager” describes a level of functionality that is well beyond simple data management. The data manager facility applies technologies ranging from relational data bases, neural networks [26], and fuzzy systems [27] to expert systems [9], [26]. The problems it addresses can be variously characterized as signal, data, or information processing.

In the past, improving the dry end of a sonar system was synonymous with the development of new signal-processing algorithms and faster hardware. While advances will continue to be made in these areas, future developments in data (contact) management represent one of the most exciting avenues of research in the development of high-performance systems.

One aspect of this development is associated with the operational requirement by the operator to be able to assess numerous detected signals rapidly in terms of localization, tracking, and classification in order to pass the necessary information up through the chain of command to enable tactical decisions to be made in a timely manner. Thus, an assigned task for a data manager would be to provide the operator with quick and easy access to both the output of the signal processor, which is called acoustic display, and the tactical display, which will show localization and tracking information through graphical interaction between the acoustic and tactical displays.

It is apparent from the above that for a next-generation sonar system, emphasis should be placed on the degree of interaction between the operator and the system through
A simplified overview of integration of four different levels of information from sensor level to a command and control level for a sonar system. These levels consist mainly of 1) navigation and nonacoustic data from receiving sensor arrays, 2) environmental information to access the medium’s influence on sonar system performance, 3) signal processing of received acoustic signals that provides parameter estimation in terms of bearing, range, and temporal spectral estimates for detected signals, and 4) signal following (tracking) and localization of detected targets.

Even though the processing steps of radar and airborne systems associated with localization, tracking, and classification have conceptual similarities with those of a sonar system, the processing techniques that have been successfully applied in airborne systems have not been successful with sonar systems. This is a typical situation that indicates how hostile, in terms of signal propagation characteristics, the underwater environment is with respect to the atmospheric environment. It is our belief that technologies associated with data fusion, neural networks, knowledge-based systems, and automated parameter estimation will provide solutions to the very difficult operational sonar problem regarding localization, tracking, and classification.

In summary, the main focus of the assigned tasks of a modern sonar system would vary from the detection of signals of interest in the open ocean to very quiet signals in very cluttered underwater environments, which could be shallow coastal sea areas. These varying degrees of complexity of the above tasks, however, can be grouped together quantitatively, and this will be the topic of our discussion in the following section.
D. The Sonar Problem

A convenient and accurate integration of the wide variety of effects of the underwater environment, the target’s characteristics, and the sonar system’s design parameters is provided by the sonar equation [8]. Since World War II, the sonar equation has been used extensively to predict the detection performance and to assist in the design of a sonar system. It combines, in logarithmic units (i.e., units of decibels relative to the standard reference of energy flux density of rms pressure of $1\mu Pa$ integrated over a period of one second), the following terms:

$$\left(S - TL\right) - \left(N_e - AG\right) - DT \geq 0$$  \hspace{1cm} (1)

which define signal excess where:

$S$ source energy flux density at a range of 1 m from the source;

$TL$ propagation loss for the range separating the source and the sonar array receiver; thus, the term ($S - TL$) expresses the recorded signal energy flux density at the receiving array;

$N_e$ noise energy flux density at the receiving array;

$AG$ array gain that provides a quantitative measure of the coherence of the signal of interest with respect to the coherence of the noise across the line array (see Section III-B);

$DT$ detection threshold associated with the decision process that defines the SNR at the receiver input required for a specified probability of detection and false alarm.

A detailed discussion of the $DT$ term and the associated statistics are given in [8] and [28]–[30]. Very briefly, the parameters that define the detection threshold values for a sonar system are the following.

- The time-bandwidth product, which defines the integration time of signal processing. This product consists of the term $T$, which is the time-series length for coherent processing such as the fast Fourier transform (FFT) and the incoherent averaging of the power spectra over $K$ successive blocks. The reciprocal $1/T$ of the FFT length defines the bandwidth of a single frequency cell. An optimum signal-processing scheme should match the acoustic signal’s bandwidth with that of the FFT length $T$ in order to achieve the predicted $DT$ values.

- The probabilities of detection $P_D$ and false alarm $P_{FA}$, which define the confidence that the correct decision has been made.

Improved processing gain can be achieved by incorporating segment overlap, windowing, and FFT zero extension, as discussed by Welch [31] and Harris [32]. In summary, the definition of $DT$ is given by [8]

$$DT = 10 \log \frac{S}{N_e} = 5 \log \left(\frac{d \cdot BW}{t}\right)$$  \hspace{1cm} (2)

where $N_e$ is the noise power in a 1-Hz band, $S$ is the signal power in bandwidth $BW$, $t$ is the integration period in displays during which the signal is present, and $d$ is the detection index of the ROC curves defined for specific values of $P_D$ and $P_{FA}$ [8], [28]. Typical values for the above parameters in the term $DT$ that are considered in real-time sonar systems are: $BW = O(10^{-2})$ Hz, $d = 20$, for $P_D = 50\%$, $P_{FA} = 0.1\%$ and $t = O(10^{2})$ s.

For values of $TL$ for which (1) becomes an equality, we have

$$\text{FoM} = S - (N_e - AG) + DT$$  \hspace{1cm} (3)

where the new term FoM (figure of merit) equals the transmission loss $TL$, and gives an indication of the range at which a sonar can detect its target.

The noise term $N_e$ in (1) includes the total or composite noise received at the array input of a sonar system and is the linear sum of all the components of the noise processes, which are assumed independent. Detailed discussions of the noise processes related to sonar systems are beyond the scope of this paper, however, and readers interested in these noise processes can refer to other publications on the topic [8], [33]–[39].

When taking the sonar equation as the common guide as to whether the processing concepts of a sonar system will give improved performance against very quiet targets, the following issues become very important and appropriate.

- During sonar operations, the terms $S$, $TL$, and $DT$ are beyond the sonar operators’ control because $S$ and $TL$ are given as parameters of the sonar problem and $DT$ is associated mainly with the design of the array receiver. The signal-processing parameters in (2) that influence $DT$ are adjusted by the sonar operators so that $DT$ will have the maximum positive impact in improving the FoM of a sonar system.

- The quantity $(N_e - AG)$ in (1) and (3), however, provides opportunities for sonar performance improvements by increasing the term $AG$ (e.g., deploying large-size array receivers or using new signal-processing schemes) and by minimizing the term $N_e$ (e.g., using adaptive processing by taking into consideration the directional characteristics of the noise field and by reducing the impact of the sensor array’s self-noise levels).

Our emphasis in this paper will be focused on the minimization of the quantity $(N_e - AG)$. This will result in new signal-processing schemes in order to achieve a desired level of performance improvement for the specific case of a line array sonar system.

II. THEORETICAL REMARKS

Sonar operations can be carried out by a wide variety of naval platforms, as shown in Fig. 3. This includes surface vessels, submarines, and airborne systems, such as airplanes and helicopters. Shown also in Fig. 3 is a schematic representation of active and passive sonar operations in an underwater sea environment. Active sonar
operations involve the transmission of well-defined acoustic signals, called replicas, which illuminate targets in an underwater sea area. The reflected acoustic energy from a target provides the sonar array receiver with a basis for detection and estimation. Passive sonar operations base their detection and estimation on acoustic sounds, which emanate from submarines and ships. Thus, in passive systems, only the receiving sensor array is under the control of the sonar operators. In this case, major limitations in detection and classification result from imprecise knowledge of the characteristics of the target radiated acoustic sounds.

The passive sonar concept can be made clearer by comparing sonar systems with radars, which are always active. Another major difference between the two systems arises from the fact that sonar system performance is more affected than that of radar systems by the underwater medium propagation characteristics. All the above issues have been discussed in several review articles [1]–[4] that form a good basis for interested readers to become familiar with “mainstream” sonar signal-processing developments. Therefore, discussions of issues of conventional sonar signal processing, detection, estimation, and influence of medium on sonar system performance are beyond the scope of this paper. Only a very brief overview of the above issues will be highlighted in this section in order to define the basic terminology required for the presentation of the main theme of this paper.

Let us start with a basic system model that reflects the interrelationships between the target, the underwater sea environment (medium), and the receiving sensor array of a sonar system. A schematic diagram of this basic system is shown in Fig. 4, where sonar signal processing is shown to be two dimensional (2-D) [1], [12], [40] in the sense that it involves both temporal and spatial spectral analysis. The temporal processing provides spectral characteristics that are used for target classification and the spatial processing provides estimates of the directional characteristics (i.e., bearing and possibly range) of a detected signal. Thus, space-time processing is the fundamental processing concept in sonar systems, and it will be the subject of the next section.

### A. Space-Time Processing

Let us consider a combination of \( N \) equally spaced acoustic transducers in a linear array, which may form a towed or hull mounted array system that can be used to estimate the directional properties of echoes and acoustic signals. As shown in Fig. 4, a direct analogy between sampling in space and sampling in time is a natural extension of the sampling theory in space-time signal representation and this type of space-time sampling is the basis in array design that provides a description of a sonar array system response. When the sensors are arbitrarily distributed, each element will have an added degree of freedom, which is its position along the axis of the array. This is analogous to nonuniform temporal sampling of a signal. In this paper, we restrict our discussion to line array systems. Sources of sound that are of interest in sonar system applications are harmonic narrowband and broadband and satisfy the wave equation [1], [40]. Furthermore, their solutions have the property that their associated temporal-spatial characteristics are separable [40]. Therefore, measurements of the pressure field \( z(\vec{r}, t) \), which is excited by acoustic source signals, provide the spatial-temporal output response, designated by \( x(\vec{r}, t) \) of the measurement system. The vector \( \vec{r} \) refers to the source-sensor relative position and \( t \) is the time. The output response \( x(\vec{r}, t) \) is the convolution of \( z(\vec{r}, t) \) with the line array system response \( h(\vec{r}, t) \) [40], [41]

\[
x(\vec{r}, t) = h(\vec{r}, t) \odot z(\vec{r}, t)
\]  

(4)

where \( \odot \) refers to convolution. Since \( z(\vec{r}, t) \) is defined at the input of the receiver, it is the convolution of the source’s
characteristics $y(\tau, t)$ with the underwater medium’s response $\psi(\tau, t)$

$$z(\tau, t) = \psi(\tau, t) \otimes y(\tau, t). \quad (5)$$

Fourier transformation of (4) provides

$$X(\omega, \vec{k}) = H(\omega, \vec{k}) \cdot \{\Psi(\omega, \vec{k}) \cdot Y(\omega, \vec{k})\} \quad (6)$$

where $\omega, \vec{k}$ are the frequency and wave-number parameters of the temporal and spatial spectrums of the transform functions in (4) and (5). Signal processing, in terms of beam-forming operations, of the receiver’s output $x(\tau, t)$ provides estimates of the source bearing and possibly of the source range. This is a well-understood concept of the forward problem, which is concerned with determining the parameters of the received signal $x(\tau, t)$ given that we have information about the other two functions $z(\tau, t)$ and $h(\tau, t)$ [4]. The inverse problem is concerned with determining the parameters of the impulse response of the medium $\psi(\tau, t)$ by extracting information from the received signal $x(\tau, t)$ assuming that the function $h(\tau, t)$ is known [4]. The sonar and radar problems, however, are quite complex and include both forward and inverse problem operations. In particular, detection, estimation, and tracking-localization processes of sonar systems are typical examples of the forward problem, while target classification for passive–active sonars is a typical example of the inverse problem. In general, the inverse problem is a computationally very costly operation. Typical examples in acoustic signal processing are seismic deconvolution and acoustic tomography.

**B. Definition of Basic Parameters**

This section outlines the context in which the sonar problem can be viewed in terms of models of acoustic signals and noise fields. The signal-processing concepts that are discussed in this paper have been included in sonar and radar investigations with sensor arrays having circular, planar, cylindrical, and spherical geometric configurations [101]. For geometrical simplicity and without any loss of generality, we consider here an $N$-hydrophone line array receiver with sensor spacing $\delta$, as shown in Fig. 4. The output of the $n$th sensor is a time series denoted by $x_n(t_j)$, where $(j = 1, \cdots, M)$ are the time samples for each sensor time series. The symbol “*” denotes complex conjugate transposition so that $\vec{z}^*$ is the row vector of the received $N$-hydrophone time series $\{x_n(t_j), n = 1, 2, \cdots, N\}$.

Then $x_n(t_j) = s_n(t_j) + \epsilon_n(t_j)$, where $s_n(t_j), \epsilon_n(t_j)$ are the signal and noise components in the received sensor time series. $\vec{s}, \vec{\epsilon}$ denote the column vectors of the signal and noise components of the vector $\vec{x}$ of the sensor outputs (i.e., $\vec{x} = \vec{s} + \vec{\epsilon}$). $X_n(f) = \sum_{j=1}^{M} x_n(t_j) \exp(-j2\pi f t_j)$ is the Fourier transform of $x_n(t_j)$ at the signal with frequency $f$, $c = f\lambda$ is the speed of sound in the underwater medium and $\lambda$ is the wavelength of the frequency $f$. $S = E[\vec{z} \cdot \vec{z}^*]$ is the spatial correlation matrix of the signal vector $\vec{s}$, whose $\eta$th element is expressed by

$$s_n(t_j) = s_n[t_j + \tau_n(\theta)] \quad (7)$$

$E\{\cdots\}$ denotes expectation and

$$\tau_n(\theta) = (n - 1)\delta \cos \theta/c \quad (8)$$
is the time delay between the first and the $q$th hydrophone of the line array for an incoming plane wave with direction of propagation $\theta$, as illustrated in Fig. 4. In frequency domain, the spatial correlation matrix $S$ for the plane wave signal $s_n(t)$ is defined by

$$S(f_i, \theta) = A_n(f_i)\overline{D}(f_i, \theta)D(f_i, \theta)$$

(9)

where $A_n(f_i)$ is the power spectral density of $s_n(t)$ for the $q$th frequency bin and $\overline{D}(f_i, \theta)$ is the steering vector having its $n$th phase term for the plane wave arrival, with angle $\theta$ being expressed by

$$d_n(f_i, \theta) = \exp \left[ j2\pi(i-1)f_s\tau_n(\theta) \right]$$

(10)

where $f_s$ is the sampling frequency. Then matrix $S(f_i, \theta)$ has its $n$th row and $m$th column defined by $S_{nm}(f_i, \theta) = A_n(f_i)d_n(f_i, \theta)\overline{m}(f_i, \theta)$. Moreover, $R(f_i)$ is the spatial correlation matrix of received hydrophone time series with elements $R_{nm}(f_i, \theta)$. $R_n(f_i) = \sigma_n^2(f_i)R_{nn}(f_i)$ is the spatial correlation matrix of the noise for the $q$th frequency bin, with $\sigma_n^2(f_i)$ being the power spectral density of the noise $e_n(t_i)$. In what is considered an estimation procedure being the power spectral density of the sensor array in order to optimize the array $n$th column defined by $f_i$. $R_n(f_i)$ is the steering vector having its $n$th phase term for the plane wave arrival, with angle $\theta$ being expressed by

$$d_n(f_i, \theta) = \exp \left[ j2\pi(i-1)f_s\tau_n(\theta) \right]$$

(10)

where $f_s$ is the sampling frequency. Then matrix $S(f_i, \theta)$ has its $n$th row and $m$th column defined by $S_{nm}(f_i, \theta) = A_n(f_i)d_n(f_i, \theta)\overline{m}(f_i, \theta)$. Moreover, $R(f_i)$ is the spatial correlation matrix of received hydrophone time series with elements $R_{nm}(f_i, \theta)$. $R_n(f_i) = \sigma_n^2(f_i)R_{nn}(f_i)$ is the spatial correlation matrix of the noise for the $q$th frequency bin, with $\sigma_n^2(f_i)$ being the power spectral density of the noise $e_n(t_i)$. In what is considered an estimation procedure in this paper, the associated problem of detection is defined in the classical sense as a hypothesis test that provides a detection probability and a probability of false alarm. This choice of definition is based on the standard CFAR processor, which is based on the Neyman–Pearson criterion [28]. The CFAR processor provides an estimate of the ambient noise or clutter level so that the threshold can be varied dynamically to stabilize the false alarm rate. Ambient noise estimates for the CFAR processor are provided mainly by noise normalization techniques [42]–[45] that account for the slowly varying changes in the background noise or clutter. The above estimates of the ambient noise are based upon the average value of the received signal, the desired probability of detection, and the probability of false alarms.

Furthermore, optimum beam forming, which is basically a spatial filter, requires the beam-forming filter coefficients to be chosen based on the covariance matrix of the received data by the $N$-sensor array in order to optimize the array response [46], [47]. The family of algorithms for optimum beam forming that use the characteristics of the noise are called adaptive beam formers [2], [11], [12], [46]–[49]. A detailed definition of an adaptation process requires knowledge of the correlated noise’s covariance matrix $R(f_i)$. If the required knowledge of the noise’s characteristics is inaccurate, however, the performance of the optimum beam former will degrade dramatically [12], [49]. As an example, the case of cancellation of the desired signal is often typical and significant in adaptive beam-forming applications [12], [50]. This suggests that the implementation of useful adaptive beam formers in real-time operational systems is not a trivial task. The existence of numerous articles on adaptive beam forming suggests the dimensions of the difficulties associated with this kind of implementation.

To minimize the generic nature of the problems associated with adaptive beam forming, the concept of partially adaptive beam-former design was introduced. This concept reduces the degrees of freedom, which results in lowering the computational requirements and often improving the adaptive response time [11], [12]. However, the penalty associated with the reduction of the degrees of freedom in partially adaptive beam formers is that they cannot converge to the same optimum solution as the fully adaptive beam former.

Although a review of the various adaptive beam formers would seem relevant at this point, we believe that this is not necessary since there are excellent review articles [2], [4], [11]–[13], [24] that summarize the points that have been considered for this experimental study. There are two main families of adaptive beam formers: GSC’s and LCMV’s. A special case of the LCMV is Capon’s maximum likelihood method [48], which is called MVDR [11], [12], [48], [49]. This algorithm has proven to be one of the more robust of the adaptive array beam formers and has been used by numerous researchers as a basis to derive other variants of MVDR [12]. In this paper, we will address implementation issues for various partially adaptive variants of the MVDR method and a GSC adaptive beam former [51]–[53], which are discussed in Section III-C.

At this point, a brief discussion on the fundamentals of detection and estimation processes is required in order to address implementation issues of signal-processing schemes in sonar systems.

C. Detection and Estimation

The problem of detection [28]–[30] is much simpler than the problem of estimating one or more parameters of a detected signal. Classical decision theory [8], [28]–[30], [54] treats signal detection and signal estimation as separate and distinct operations. A detection decision as to the presence or absence of the signal is regarded as taking place independently of any signal parameter or wave-form estimation that may be indicated as the result of detection decision. However, interest in joint or simultaneous detection and estimation of signals arises frequently. Middleton and Esposito [55] have formulated the problem of simultaneous optimum detection and estimation of signals in noise by viewing estimation as a generalized detection process. Practical considerations, however, require different cost functions for each process [55]. As a result, it is more effective to retain the usual distinction between detection and estimation.

Estimation, in passive sonar systems, includes both the temporal and spatial structure of an observed signal field. For active systems, correlation processing and Doppler (for moving target indications) are major concerns that define the critical distinction between these two approaches (i.e., passive, active) to sonar processing. In this paper, we restrict our discussion to topics related to spatial signal processing for estimating signal parameters. However, spatial signal processing has a direct representation that is analogous to the frequency-domain representation of temporal signals. Therefore, the spatial signal-processing concepts discussed here have direct applications to temporal spectral analysis.
Typically, the performance of an estimator is represented as the variance in the estimated parameters. Theoretical bounds associated with this performance analysis are specified by the Cramér–Rao bound [28]–[30], and that has led to major research efforts by the sonar signal-processing community in order to define the idea of an optimum processor for discrete sensor arrays [17], [19], [56]–[60]. If the a priori probability of detection is close to unity, then the minimum variance achievable by any unbiased estimator is provided by the Cramér–Rao lower bound (CRLB) [28], [29], [55]. In this case, if there exists a signal processor to achieve the CRLB, it will be the maximum-likelihood estimation technique. The above requirement associated with the a priori probability of detection is very essential because if it is less than one, then the estimation is biased and the theoretical CRLB’s do not apply. This general framework of optimality is very essential in order to account for Middleton’s [29] warning that a system optimized for the one function (detection or estimation) may not be necessarily optimized for the other.

For a given model describing the received signal by a sonar system, the CRLB analysis can be used as a tool to define the information inherent in a sonar system. This is an important step related to the development of the signal-processing concept for a sonar system as well as in defining the optimum sensor configuration arrangement under which we can achieve, in terms of system performance, the optimum estimation of signal parameters of our interest. This approach has been applied successfully to various studies related to the present development [17], [19], [56]–[60].

The next question that needs to be addressed is about the unbiased estimator that can exploit this available information and provide results asymptotically reaching the CRLB’s. For each estimator, it is well known that there is a range of SNR in which the variance of the estimates rises very rapidly as SNR decreases. This effect, which is called the threshold effect of the estimator, determines the range of SNR of the received signals for which the parameter estimates can be accepted. In passive sonar systems, the SNR of signals of interest is often quite low and probably below the threshold value of an estimator. In this case, high-frequency resolution in both time and spatial domains for the parameter estimation of narrowband signals is required. In other words, the threshold effect of an estimator determines the frequency resolution for processing and the size of the towed array required in order to detect and estimate signals of interest that have very low SNR [17], [18], [53], [61], [62]. The CRLB analysis has been used in the present study to evaluate and compare the performance of the various nonconventional processing schemes [17], [18], [53], [61], [62] that have been considered for implementation in the generic beam-forming structure to be discussed in Section IV-A.

III. Optimum Estimators for Sonar Signal Processing

The purpose of this section is to outline very briefly the processing schemes that have been considered in this experimental study. These schemes are conventional, adaptive, and synthetic-aperture methods, which are introduced in Sections III-A, III-C, III-D, and III-F by outlining their sonar-related implementation considerations. Briefly, these considerations include mainly estimation (after detection) of the source’s bearing, which is the main concern in sonar array systems because in most of the sonar applications, the acoustic signal’s wave fronts tend to be planar, which assumes distant sources. Passive ranging by measurement of wave-front curvature is not appropriate for the far-field problem. The range estimate of a distant source, in this case, must be determined by various target-motion analysis methods discussed in Section V-A, which addresses the localization-tracking performance of nonconventional beam formers with real data. In general, sonar array processing includes a large number of algorithms and systems that are quite diverse in concept. There is a basic point that is common in all of them, however, and this is the beam-forming process, which we are going to examine next.

A. Conventional Beam Forming

Previous studies [63] have shown that the conventional beam former (CBF) without shading is the optimum beam former for bearing estimation, and its variance estimates achieve the CRLB bounds. The narrow-band CBF is defined by [12]

\[ B(f, \theta_s) = D^* (f, \theta_s) R(f, \theta_s) D(f, \theta_s) \]  

(11)

where \( d_{n}(f, \theta_s) \) is the \( n \)-th term of the steering vector \( D(f, \theta_s) \) for the beam steering direction \( \theta_s \), as expressed by (10). Equation (11) is basically a mathematical interpretation of Fig. 4 and shows that a line array is basically a spatial filter because by steering a beam in a particular direction, we spatially filter the signal coming from that direction, as illustrated in Fig. 4. On the other hand, (11) is fundamentally a discrete Fourier transform relationship between the hydrophone weightings and the beam pattern of the line array, and as such it is computationally a very efficient operation. However, (11) can be generalized for nonlinear two- and three-dimensional arrays, which is discussed in [101].

As an example, let us consider a distant monochromatic source. Then the plane wave signal arrival from the direction \( \theta \) received by an \( N \)-hydrophone line array is expressed by (10). The plane-wave response to the above signal of this line array steered at direction \( \theta_s \) can be written as follows:

\[ U(f, \theta_s) = \sum_{n=1}^{N} X_n(f) d_n(f, \theta_s) \]  

(12)

and the beam-power pattern \( B(f, \theta_s) \) is given by \( B(f, \theta_s) = |U(f, \theta_s) P^*(f, \theta_s) |^2 \). Then, the beam-power pattern \( B(f, \theta_s) \) takes the form

\[ B(f, \theta_s) = \sum_{n=1}^{N} \sum_{m=1}^{N} X_n(f) X_m^*(f) \exp \left[ j2\pi f \frac{\delta_{nm} \cos \theta_s}{c} \right] \]  

(13)
where \( \delta_{nm} \) is the spacing \( \delta(n-m) \) between the \( n \)th and \( m \)th hydrophones. As a result of (10), the expression for the beam-power pattern \( B(f, \theta_s) \), is reduced to

\[
B(f, \theta_s) = \left( \frac{\sin N \frac{2 \pi f}{\lambda} (\sin \theta_n - \sin \theta)}{\sin N \frac{2 \pi f}{\lambda} (\sin \theta_n - \sin \theta)} \right)^2.
\]  

(14)

Let us consider, for simplicity, that the source bearing \( \theta \) is at array broadside, \( \delta = \lambda/2 \), and \( L = (N-1)\delta \) is the array size. Then (11) is modified as [3], [40]

\[
B(f, \theta_s) = \frac{N^2 \sin^2 \left( \frac{\pi f \sin \theta_s}{\lambda} \right)}{(\pi f \lambda)^2} \quad (15)
\]

which is the far-field radiation or directivity pattern of the line array as opposed to near-field regions. The results in (14) and (15) are for a perfectly coherent incident acoustic signal, and an increase in array size \( L \) results in additional power output and a reduction in beamwidth. The side-lobe structure of the directivity pattern of a line array, which is expressed by (14), can be suppressed at the expense of a beamwidth increase by applying different weights. The selection of these weights will act as spatial filter coefficients with optimum performance [4], [11], [12].

There are two different approaches to select the above weights: pattern optimization and gain optimization. For pattern optimization, the desired array response pattern \( B(f, \theta_s) \) is selected first. A desired pattern is usually one with a narrow main lobe and low side lobes. The weighting or shading coefficients in this case are real numbers from well-known window functions that modify the array response pattern. Harris' review [32] on the use of windows in discrete Fourier transforms and temporal spectral analysis is directly applicable in this case to spatial spectral analysis for towed line array applications.

Using the approximation \( \sin \theta \approx \theta \) for small \( \theta \) at array broadside, the first null in (12) occurs at \( \pi L \sin \theta / \lambda = \pi \) or \( \Delta \theta = L/\lambda \approx 1 \). The major conclusion drawn here for line array applications is that [3], [40]

\[
\Delta \theta \approx \lambda / L \quad \text{and} \quad \Delta f \times T = 1
\]  

(16)

where \( T = M/F_s \) is the hydrophone time-series length. Both the above relations in (16) express the well-known temporal and spatial resolution limitations in line array applications that form the driving force and motivation for adaptive and synthetic-aperture signal processing that we will discuss later.

An additional constraint for sonar applications requires that the frequency resolution \( \Delta f \) of the hydrophone time series for spatial spectral analysis that is based on FFT beam-forming processing must be such that

\[
\Delta f \times \frac{L}{c} \ll 1
\]  

(17)

in order to satisfy frequency quantization effects associated with discrete frequency-domain beam forming following the FFT of sensor data [11], [64]. This is because in conventional beam forming, finite-duration impulse response (FIR) filters are used to provide realizations in designing digital phase shifters for beam steering. Since fast-convolution signal-processing operations are part of the processing flow of a sonar signal processor, the effective beam-forming filter length needs to be considered as the overlap size between successive snapshots. In this way, the overlap process will account for the wraparound errors that arise in the fast-convolution processing [65]–[67]. It has been shown [64] that an approximate estimate of the effective beam-forming filter length is provided by (15) and (17).

Because of the linearity of the conventional beam-forming process, an exact equivalence of the frequency-domain narrow-band beam former with that of the time-domain beam former for broad-band signals can be derived [64], [68], [69]. Based on the model of Fig. 4, the time-domain beam former is simply a time delaying [69] and summing process across the hydrophones of the line array, which is expressed by

\[
\xi(\theta_s, t) = \sum_{n=1}^{N} x_n(t_i - \tau_s),
\]  

(18)

Since \( \xi(\theta_s, t_i) = \text{IFFT} \left\{ |B(f, \theta_s)| \right\} \), by using FFT’s and fast convolution procedures, continuous beam-time sequences can be obtained at the output of the frequency-domain beam former [64]. This is a very useful operation when the implementation of beam-forming processors in sonar systems is considered.

The beam-forming operation in (18) is not restricted only for plane-wave signals. More specifically, consider an acoustic source at the near field of a line array with \( r_s \), the source range and \( \theta \) its bearing. Then the time delay for steering at \( \theta \) is

\[
\tau_s = (r_s^2 + d_{nm}^2 - 2 r_s d_{nm} \cos \theta)^{1/2} / c. \quad (19)
\]

As a result of (19), the steering vector \( d_{nm}(f, \theta_s) = \exp[j2\pi f \tau_s] \) will include two parameters of interest, the bearing \( \theta \) and range \( r_s \) of the source. In this case, the beam former is called a focused beam former. There are, however, practical considerations restricting the application of the focused beam former in passive sonar line array systems, and these have to do with the fact that effective range focusing by a beam former requires extremely long arrays.

\section*{B. Array Gain}

It was discussed in Section I-D that the performance of a sonar array receiver to an acoustic signal embodied in a noise field is characterized by the “array gain” parameter, \( AG \), a term in (1). This parameter is defined by

\[
AG = 10 \log \frac{\sum_{n=1}^{N} \sum_{m=1}^{N} \rho_{nm}(f, \delta_{nm})}{\sum_{n=1}^{N} \sum_{m=1}^{N} \rho_{nm}(f, \delta_{nm})} \quad (20)
\]

where the cross-correlation coefficients \( \rho_{nm}(f, \delta_{nm}) \) are given by

\[
\rho_{nm}(f, \delta_{nm}) = R_{nm}(f, \delta_{nm}) / X^2(f) \quad (21)
\]
where $X^2(f)$ is the mean acoustic intensity of hydrophone time sequences at the frequency bin $f$ and $\rho_{mm}(f, \delta_{mm})$, $\rho_{x,m}(f, \delta_{mm})$ denote the normalized cross-correlation coefficients of the signal and noise field [8], [41], respectively. If the noise field is isotropic, the denominator in (20) is equal to $N$ because the nondiagonal terms of the cross-correlation matrix for the noise field are negligible. For perfect spatial coherence across the line array, the normalized cross-correlation coefficients are $\rho_{mm}(f, \delta_{mm}) \cong 1$ and the expected values of the array gain estimates are $AG = 10 \times \log_2 N$. For the general case of isotropic noise and for frequencies smaller than the towed array’s design frequency, $AG$ is reduced to the quantity called the directivity index (DI) $DI = 10 \times \log_2[(N-1)\delta/\lambda/2]$. When $\delta \ll \lambda$ and the conventional beam-forming processing is employed, (16) indicates that the deployment of very long line arrays is required in order to achieve sufficient array gain and angular resolution for precise bearing estimates. Practical deployment considerations, however, usually limit the overall dimensions of a hull mounted line or towed array. In addition, the medium’s spatial coherence [41] sets an upper limit on the effective towed array length. In general, the medium’s spatial coherence length is on the order of $\mathcal{O}(10^2)\lambda$ [40], [41], [71], [72]. In addition, very long towed arrays suffer degradation in the array gain due to array shape deformation and increased levels of self-noise [34], [73]–[78].

Alternatives to large-aperture sonar arrays are signal-processing schemes discussed in [9]. Theoretical and experimental investigations have shown that bearing resolution and detectability of weak signals in the presence of strong interferences can be improved by applying nonconventional beam formers such as adaptive beam forming [2], [11]–[13], [23], [24], [46]–[54], [79]–[84], high-resolution (linear prediction) techniques [61], [63], [71]–[82], [85]–[96], or acoustic synthetic-aperture processing [14]–[20], [22], [62], [97] to the hydrophone time series of deployed short sonar arrays.

Moreover, a first-order analysis of beam-forming structures usually ignores a whole host of practical issues, which can severely compromise actual achieved array gain. For the signals of interest, which are embodied in anisotropic noise fields that consist of partially directional correlated noise due to the distant shipping, one of the most important issues, shown in (20), is the impact of the correlation properties of the anisotropic noise on the array gain of a sonar system. This impact is quite severe for conventional beam formers because the correlation properties of the noise field are ignored in the mainstream sonar processing schemes.

The focus of this implementation study is on defining an integrated advanced beam-forming structure for real-time systems. This processing structure consists of a collection of various nonconventional beam-forming algorithms that recent investigations have shown to provide improved array-gain performance in anisotropic noise fields. In the following two sections, we will discuss very briefly the two major processing schemes, adaptive and acoustic synthetic-aperture schemes, that have played an important role in this investigation.

C. Adaptive Beam Formers

1) MVDR: The goal is to optimize the beam-former response so that the output contains minimal contributions due to noise and signals arriving from directions other than the desired signal direction. For this optimization procedure, it is desired to find a linear filter vector $\mathbf{W}(f_i, \theta)$, which is a solution to the constrained minimization problem that allows signals from the look direction to pass with a specified gain [11], [12].

Minimize

$$
\sigma_{\mathbf{W}}^2 = \mathbf{W}^t(f_i, \theta) \mathbf{R}(f_i) \mathbf{W}(f_i, \theta)
$$

subject to

$$
\mathbf{W}^t(f_i, \theta) \mathbf{D}(f_i, \theta) = 1
$$

where $\mathbf{D}(f_i, \theta)$ is the conventional steering vector based on (10). The solution is given by

$$
\mathbf{W}(f_i, \theta) = \frac{\mathbf{R}^{-1}(f_i) \mathbf{D}(f_i, \theta)}{\mathbf{D}^t(f_i, \theta) \mathbf{R}^{-1}(f_i) \mathbf{D}(f_i, \theta)}.
$$

The above solution provides the adaptive steering vectors for beam forming the received signals by the $N$-hydrophone line array. Then in frequency domain, an adaptive beam at a steering $\theta_s$ is defined by

$$
b(f_i, \theta_s) = \mathbf{W}^t(f_i, \theta_s) \mathbf{X}(f_i)
$$

and the corresponding conventional beams are provided by (12).

2) GSC: The GSC [12] is an alternative approach to the MVDR method. It reduces the adaptive problem to an unconstrained minimization process. The GSC formulation produces a much less computationally intensive implementation. In general, GSC implementations have complexity $\mathcal{O}(N^2)$, as compared to $\mathcal{O}(N^3)$ for MVDR implementations, where $N$ is the number of sensors used in the processing. The basis of the reformulation of the problem is the decomposition of the adaptive filter vector $\mathbf{W}(f_i, \theta)$ into two orthogonal components $\mathbf{w}$ and $-\mathbf{w}$, where $\mathbf{w}$ and $\mathbf{w}$ lie in the range and the null space of the constraint of (22), such that $\mathbf{W}(f_i, \theta) = \mathbf{w}(f_i, \theta) - \mathbf{w}(f_i, \theta)$. A matrix $\mathbf{C}$, which is called a signal blocking matrix, may be computed from $\mathbf{C} \mathbf{T} = 0$ where $\mathbf{T}$ is a vector of ones. This matrix $\mathbf{C}$, whose columns form a basis for the null space of the constraint of (22), will satisfy $\mathbf{v} = \mathbf{C} \mathbf{u}$, where $\mathbf{u}$ is defined by (26). The adaptive filter vector may now be defined as $\mathbf{W} = \mathbf{w} - \mathbf{C} \mathbf{u}$ and yields the realization shown in Fig. 5. Then the problem is reduced to the following.

Minimize

$$
\sigma_{\mathbf{u}}^2 = \{[\mathbf{w} - \mathbf{C} \mathbf{u}]^t \mathbf{R} \mathbf{w} - \mathbf{C} \mathbf{u}]\}
$$

which is satisfied by

$$
\mathbf{u}_{\text{opt}} = (\mathbf{C}^t \mathbf{R} \mathbf{C})^{-1} \mathbf{C}^t \mathbf{R} \mathbf{w}
$$

$\mathbf{u}_{\text{opt}}$ being the value of the weights at convergence.

The Griffiths–Jim GSC, in combination with the NLMS adaptive algorithm, has been shown to yield near instantaneous convergence [51], [98], [99]. Fig. 5 shows the
3) STMV Broad-Band Adaptive: Krolik and Swingler [83] have shown that the convergence time for broad-band source location can be reduced by using the space-time statistic called the STCM. This method achieves significantly shorter convergence times than adaptive algorithms that are based on the narrow-band cross-spectral density matrix (CSDM) [12] without sacrificing spatial resolution. In fact, the number of statistical degrees of freedom available to estimate the STCM is approximately the time-bandwidth product \((T \times BW)\), as opposed to the observation time \((T = M/F_s, F_s\) being the sampling frequency) in CSDM methods. This provides an improvement of approximately \(BW\), the size of the broad-band source bandwidth, in convergence time. The conventional beam former’s output in frequency domain is shown by (12). The corresponding time-domain conventional beam-former output \(\xi(t_s, \theta_s)\) is the weighted sum of the steered sensor outputs, as expressed by (18). Then, the expected broad-band beam power \(B(\theta)\) is given by

\[
B(\theta) = E\{[\xi(t_s, t)]\} = \Re E\{|x_\theta(t_s, t)|^2\} = \Re \mathcal{H}^{-1}(15)
\]

where the vector \(\mathcal{H}\) includes the weights for spatial shading, as discussed in Section III-A.

The term

\[
\Phi(t_s, \theta_s) = E\{x(t_s, \tau_n(\theta_s)) \mathcal{X}[x(t_s, \tau_n(\theta_s))]\}
\]

(30)
is defined as the STCM in time domain and is assumed to be independent of \(t_s\) in stationary conditions. The name STCM is derived from the fact that the matrix is computed by taking the covariance of the presteered time-domain sensor outputs. Suppose \(x_n(f_k)\) is the Fourier transform of the sensor outputs \(x_n(t_s)\), assuming that the sensor outputs are approximately band limited. Under these conditions, the vector of steered (or time delayed) sensor outputs \(x_n(t_s, \tau_n(\theta_s))\) can be expressed by

\[
\mathcal{X}[x(t_s, \tau_n(\theta_s))] = \sum_{k=1}^{N} T_k(f_k, \theta_s) X(f_k) \exp(j2\pi f_k t_s)
\]

(31)

where \(T_k(f_k, \theta)\) is the diagonal steering matrix in (32), with elements identical to the elements of the conventional steering vector \(\mathcal{D}(f_k, \theta)\)

\[
T(f_k, \theta) = \begin{bmatrix}
1 & \cdots & 0 \\
0 & d_1(f_k, \theta) & \\
& \ddots & \ddots & \ddots \\
0 & \cdots & d_N(f_k, \theta)
\end{bmatrix}
\]

(32)

Then it follows directly from the above equations that

\[
\Phi(\Delta f, \theta_s) = \sum_{k=1}^{N} T(f_k, \theta_s) R(f_k) T^*(f_k, \theta_s)
\]

(33)
where the index \( k = l, l + 1, \ldots, l + H \) refers to the frequency bins in a band of interest \( \Delta f \) and \( R(f_k) \) is the CSDM for the frequency bin \( f_k \). This suggests that \( \Phi(\Delta f, \theta_\alpha) \) in (30) can be estimated from the CSDM, \( R(f_k) \), and \( T(f_k, \theta) \) expressed by (32). In the STMV, the broad-band spatial power spectral estimate \( B(\theta_k) \) is given by [83]

\[
B(\theta_k) = \left[ T^\prime \Phi(\Delta f, \theta_\alpha)^{-1} T \right]^{-1}.
\]

The STMV algorithm differs from the basic MVDR algorithm in that the former yields an STCM that is composed from a band of frequencies and the MVDR algorithm uses a CSDM that is derived from a single frequency bin. Thus, the additional degrees of freedom of STMV compared to those of CSDM provide a more robust adaptive process.

However, estimates of \( B(\theta) \) according to (34) do not provide coherent beam time series, since they represent the broad-band beam-power output of an adaptive process. In this investigation, we have modified the estimation process of the STMV matrix in order to get the complex coefficients \( \Phi(\Delta f, \theta_\alpha) \) for all the frequency bins in the band of interest.

The STMV algorithm may be used in its original form to generate an estimate of \( \Phi(\Delta f, \theta) \) for all the frequency bands \( \Delta f \) across the band of the received signal. Assuming stationarity across the frequency bins of a band \( \Delta f \), the estimate of the STMV may be considered to be approximately the same as the narrow-band estimate \( \Phi(f_0, \theta) \) for the center frequency \( f_0 \) of the band \( \Delta f \). In this case, the narrow-band adaptive coefficients may be derived from

\[
\bar{w}(f_0, \theta) = \frac{\Phi(f_0, \Delta f, \theta)^{-1} D(f_0, \theta)}{D^*(f_0, \theta) \Phi(f_0, \Delta f, \theta)^{-1} D(f_0, \theta)}. \tag{35}
\]

The phase variations of \( \bar{w}(f_0, \theta) \) across the frequency bins \( i = l, l + 1, \ldots, l + H \) (where \( H \) is the number of bins in the band \( \Delta f \)) are modeled by

\[
w_n(f_i, \theta) = \exp[2\pi f_i \Psi(\Delta f, \theta)], i = l, l + 1, \ldots, l + H \tag{36}
\]

where \( \Psi_n(\Delta f, \theta) \) is a time-delay term derived from

\[
\Psi_n(\Delta f, \theta) = F[w_n(\Delta f, \theta), 2\pi f_0]. \tag{37}
\]

Then, by using the adaptive steering weights \( w_n(\Delta f, \theta) \) that are provided by (36), the adaptive beams are formed as shown by (24). Fig. 6 shows the realization of the STMV beam former and provides a schematic representation of the basic processing steps, which include:

1) time series segmentation, overlap, and FFT, shown by the group of blocks in the top left part of the schematic diagram;
2) formation of STCM (30), (33), shown by the two blocks in the bottom left-hand side of Fig. 6;
3) inversion of covariance matrix using Cholesky factorization, estimation of adaptive steering vectors, and formation of adaptive beams in frequency domain, presented by the middle and bottom blocks on the right-hand side of Fig. 6;
4) formation of adaptive beams in time domain through inverse (I)FFT, discarding of overlap, and concatenation of segments to form continuous-beam time series, is shown in the top right-hand block.

The various indexes in Fig. 6 provide details for the implementation of the STMV processing flow in a generic computing architecture. The same figure indicates that estimates of the STCM are based on an exponentially weighted time average of the current and previous STCM, which is discussed in the next section.

D. Implementation Considerations for Adaptive Processing Schemes

In this implementation study, we form the adaptive beams in frequency domain as discussed in previous sections. Furthermore, the frequency-domain adaptive outputs, shown in Figs. 5, 6, and 12, are made equivalent to the FFT of the time-domain beam-forming outputs with proper selection of beam-forming weights and careful data partitioning. This equivalence corresponds to implementing FIR filters via circular convolution, which has also been discussed in Section III-A.

Matrix inversion is another major implementation issue for the adaptive schemes discussed in this paper. Standard numerical methods for solving systems of linear equations can be applied to solve for the adaptive weights. The range of possible algorithms includes the following.

- **Cholesky factorization** of \( R(f_i) \) and \( \Phi(\Delta f, \theta_\alpha) \) [11]. This allows the linear system to be solved by back substitution in terms of the received data vector. Note that there is no requirement to estimate the sample covariance matrix and that there is a continuous updating of an existing Cholesky factorization.

- **QR decomposition** of the received vector \( \overline{X}(f_i) \), which includes the conversion of a matrix to upper triangular form via rotations. The QR decomposition method has better stability than the Cholesky factorization algorithm but it requires twice as much computational effort as the Cholesky approach.

- **SVD method**. This is the most stable factorization technique. It requires, however, three times more computational requirements than the QR decomposition method.

In this implementation study, we have applied the Cholesky factorization and the QR decomposition techniques in order to get solutions for the adaptive weights. Our experience suggests that there are no noticeable differences in performance between the above two methods.

The main consideration, however, for implementing adaptive schemes in real-time systems is associated with the requirements derived from (23), (26), and (35), which require knowledge of second-order statistics for the noise field. Although these statistics are usually not known, they can be estimated from the received data [11], [12], [49] by
averaging a large number of independent samples of the covariance matrices \([\text{CSDM}, R(\mathbf{f}_j)]\), \([\text{STCM}, \Phi(\Delta \mathbf{f}_j, \mathbf{\theta}_q)]\), and by allowing the iteration process of the GSC scheme in (27) to converge. Thus, if \(K\) is the effective number of statistically independent samples of CSDM and STCM, then the variance on the adaptive beam output power estimator detection statistic is inversely proportional to 
\(K - N + 1\) \([11], [48]\), where \(N\) is the number of array sensors. Theoretical suggestions \([49]\) and our empirical observations suggest that this number \(K\) needs to be three to four times the size of \(N\) in order to obtain coherent-beam time series at the output of the above adaptive schemes. In other words, for arrays with a large number of sensors, the implementation of adaptive schemes as statistically optimum beam formers would require the averaging of a very large number of independent samples of CSDM and STCM in order to derive an unbiased estimate of the adaptive weights \([1]\). In practice, this is the most serious problem associated with the implementation of adaptive beam formers in real-time systems.

Owsley \([11]\) has addressed this problem with two very important contributions. His first contribution is associated with the estimation procedure of the CSDM and STCM matrices. His argument is that in practice, the CSDM and STCM matrices cannot be estimated exactly by time averaging because the received signal vector \(\mathbf{X}(\mathbf{f}_j)\) is never truly stationary and/or ergodic. As a result, the available averaging time is limited. Accordingly, one approach to the time-varying adaptive estimation of \(R(\mathbf{f}_j)\) and \(\Phi(\Delta \mathbf{f}_j, \mathbf{\theta}_q)\) at time \(t_k\) is to compute the exponentially time-averaged estimator at time \(t_k\) as

\[
R^{t_k}(\mathbf{f}_j) = \mu R^{t_{k-1}}(\mathbf{f}_j) + (1 - \mu) \mathbf{X}(\mathbf{f}_j)\mathbf{X}^H(\mathbf{f}_j) \tag{38}
\]

where \(\mu\) is a smoothing factor \((0 < \mu < 1)\) that implements the exponentially weighted time-averaging operation. The
same principle has also been applied in the GSC scheme, as expressed by (28). The use of this kind of exponential window to update the covariance matrix is a very important factor in the implementation of adaptive algorithms in real-time systems.

Owsley’s [79] second contribution deals with the dynamics of the data statistics during the convergence period of the adaptation process. As mentioned above, the implementation of an adaptive beam former with a large number of adaptive weights in a large array sonar system requires very long convergence periods that would eliminate the dynamical characteristics of the adaptive beam former to detect the time-varying characteristics of a received signal of interest. A natural way to avoid this kind of temporal stationarity limitation is to reduce the number of adaptive weights requirements. In the previous section, there was a reference to the partially adaptive beam-former design concept. Several approaches have been introduced that are based on this concept, including the implementation of the MVDR algorithm in a so-called beam space [79], [80] or the processing of a subset of the outputs of the sensors in the array [81]–[83].

The beam-space partially adaptive approach [79], [80] includes the formation of conventional beams that are used as inputs to an MVDR, STMV, or GSC adaptation process, which can be viewed as adaptive beam interpolation processes of existing steered conventional beams. Owsley’s partially adaptive beam-former concept is based on a subaperture configuration with very large percentage overlap between contiguous subapertures [79]. More specifically, a line array is divided into a number of subarrays that overlap. These subarrays are beam formed using the conventional approach, and this first stage of beam forming generates a number of sets of beams equal to the number of subarrays. The second stage of beam forming includes the implementation of the MVDR on a set of beams, which are steered in the same direction in space but each belongs to a different subarray. The above two stages of beam-forming operations are illustrated in Fig. 7. Although the above partially adaptive beam-forming designs are in frequency domain, their implementation includes broad-band as well as narrow-band applications.

Our implementation scheme of the MVDR, STMV, and GSC adaptive beam formers includes the following variants: their narrow-band implementation 1) in element space [11] and 2) in a subaperture configuration, as suggested by Owsley [79].

Passive broad-band outputs for the above adaptive beam formers are derived from the incoherent summation of the narrow-band adaptive beam-power spectral estimates for all the frequency bins in a wide band of interest. A more detailed discussion on this issue is included in Section IV, which presents various implementation aspects of signal-processing schemes in real-time systems. It is important to note, however, that under this kind of incoherent summation scheme, the broad-band adaptive outputs represent the beam outputs, only in the sense of energy content, for wide-band signals.

Coherent adaptive beam-forming processing for broad-band signals has been studied by Frost [81]. Other studies [82]–[84], such as the STMV method, have successfully attempted to downsize the computationally demanding processing requirements of Frost’s [81] algorithm. In our studies, we have considered the implementation of these relatively new broad-band adaptive processing schemes [82]–[84] in towed array sonar systems with integrated passive and active capabilities. Based on this experience, it is suggested that a successful implementation of adaptive beam formers should not be focused only on algorithm development. Instead, emphasis should be placed in developing configuration schemes equivalent to the subaperture configuration suggested by Owsley [79]. This is because the major problem in real-time adaptive beam forming is the requirement for improving the adaptive response that will allow a successful handling of the unpredictable dynamics of a real-time sonar system. We intend to address this issue again in Section V, which will present real experimental results from passive narrow- and broad-band and active real-time sonar systems, including adaptive beam formers.

E. Evaluation of Convergence Properties of Adaptive Schemes

To test the convergence properties of the various adaptive beam formers of this study, synthetic data were used that included one CW signal. The frequency of the monochromatic signal was selected to be 330 Hz and the angle of arrival was selected to be 68.9° to coincide directly with the steering direction of a beam. The SNR of the received synthetic signal was very high, 10 dB at the sensor. By definition, the adaptive beam formers allow signals in the look direction to pass undistorted while minimizing the total output power of the beam former. Therefore, in the ideal case the main beam output of the adaptive beam former should resemble the main beam output of the conventional beam former while the side beams’ outputs will be minimized to the noise level. To evaluate the convergence of the beam formers, two measurements were made. From (27), the mean square error (MSE) between the normalized main beam outputs of the adaptive beam former and the conventional beam former was measured, as was the mean of the normalized output level of the side beam, which is the MSE when compared with zero. The averaging of the errors was done with a sliding window of four snapshots to provide a time-varying average and the outputs were normalized so that the maximum output of the conventional beam former was unity.

1) Convergence Characteristics of GSC and GSC Subaperture (SA) Beam Formers: The GSC/NLMS adaptive algorithm, which was discussed in Section III-C2, and its subaperture configuration, denoted by GSC-SA/NLMS, were compared against each other to determine if the use of the subaperture configuration produced any improvement in the time required for convergence. The graph in Fig. 8(a) shows the comparison of the MSE of the main beams of both algorithms for the same step size \( \mu \), which is defined in (28). The graphs show that the convergence rates
Fig. 7. Concept of subaperture adaptive processing. Schematic diagram shows the basic steps, which include: 1) formation of J subapertures; 2) for each subaperture, formation of S conventional beams; and 3) for a given beam direction, formation of line sensor arrays that consist of J number of directional sensors (beams). The number of line arrays with directional sensors (beams) is equal to the number S steered conventional beams in each subaperture. For each line array, the directional sensor time series (beams) are provided at the input of an adaptive beam former.

of the main beams are approximately the same for both algorithms, reaching a steady-state value of MSE within a few snapshots. The value of MSE that is achieved is dictated by the misadjustment, which depends on \( \mu \). The higher MSE produced by the GSC-SA algorithm indicates that the algorithm exhibits a higher misadjustment.

The graph in Fig. 8(b) shows the output level of an immediate side beam, again for the same step size \( \mu \). The side beam was selected as the beam right next to the main beam. The GSC-SA algorithm appears superior at minimizing the output of the side beam. It reaches its convergence level almost immediately, while the GSC algorithm requires approximately 30 snapshots to reach the same level. This indicates that the GSC-SA algorithm should be superior at canceling time-varying interferers. By selecting a higher value for \( \mu \), the time required for convergence will be reduced but the MSE of the main beam will be higher.

2) Convergence Characteristics of STMV and STMV-SA Beam Formers: As with the GSC/NLMS and GSC-SA/NLMS beam formers, the STMV and STMV-SA beam formers were compared with each other to determine if there was any improvement in the time required for convergence when using the subaperture configuration.
Fig. 8. (a) MSE of the main beams of the GSC/NLMS and the GSC-SA/NLMS algorithms. (b) Side-beam levels of the above algorithms.

The graph in Fig. 9(a) shows the comparison of the MSE of the main beams of both algorithms. The graph shows that the STMV-SA algorithm reaches a steady-state value of MSE within the first few snapshots. The STMV algorithm is incapable of producing any output for at least eight snapshots as tested. Before this time, the matrices that are used to compute the adaptive steering vectors are not invertible. After this initial period, the algorithm has already reached a steady-state value of MSE. Unlike the case of the GSC algorithm, the misadjustment from subaperture processing is smaller.

Fig. 9(b) shows the output level of the side beam for both the STMV and the STMV-SA beam formers. Again, the side beam was selected as the beam right next to the main beam. As before, there is an initial period during which the STMV algorithm is computing an estimate of the STCM and is incapable of producing any output; after that period, the algorithm has reached steady state and produces lower side beams than the subaperture algorithm.

3) Signal Cancellation Effects of the Adaptive Algorithms: Testing of the adaptive algorithms of this study for signal cancellation effects was carried out with simulations that
Fig. 9. (a) MSE of the main beams of the STMV and STMV-SA algorithms. (b) Side-beam levels of the above algorithms.

included two signals arriving from 64° and 69°. All of the parameters of the signals were set to the same values for all the beam formers: conventional, GSC/NLMS, GSC-SA/NLMS, STMV, and STMV-SA. In the narrow-band outputs of the conventional beam former (which can be found in [100]), the signals appear at the frequency and beam at which they were expected. As anticipated, however, the side lobes are visible in a number of other beams. The LOFAR-gram outputs of the GSC/STMV algorithm indicated that there is signal cancellation. In each case, the algorithm failed to detect either of the two CW’s. This suggests that there is a shortcoming in the GSC/NLMS algorithm when there is strong correlation between two signal arrivals received by the line array. The narrow-band outputs of the GSC-SA/NLMS algorithm showed that in this case, the signal cancellation effects have been minimized and the two signals were detected only at the expected two beams with complete cancellation of the side-lobe structure. For the STMV beam former, the LOFAR-grams indicated a strong side-lobe structure in many other beams. However, the STMV-SA beam former successfully suppresses the side-lobe structure that was
present in the case of the STMV beam former. From all these simulations, it was obvious that the STMV-SA beam former, as a broad-band beam former, is not as robust for narrow-band applications as the GSC-S/NA/LMS.

F. Acoustic Synthetic-Aperture Processing: ETAM Algorithm

While the concept of synthetic-aperture processing has been successfully applied to aircraft and satellite radar systems, it has received limited success in passive sonar systems and wide acceptance in active side-looking sonars [14]. The realistic conditions for effective acoustic synthetic-aperture processing, which can be viewed as a scheme that converts temporal gain to spatial gain, require that successive snapshots of the acoustic signal have good cross-correlation properties in order to synthesize an extended aperture and that the tow speed fluctuations are successfully compensated by means of processing. It has been also suggested [14]–[20], [62] that the prospects for successfully extending the physical aperture of a sonar array require algorithms that are not based on the synthetic-aperture concept used in active radars.

The reported results in [15]–[20] and [62] have shown that the problem of creating an acoustic synthetic aperture is centered on the estimation of a phase-correction factor, which is used to compensate for the phase differences between sequential sonar-array measurements in order to synthesize coherently the spatial information into a synthetic aperture. When the estimates of this phase-correction factor are correct, then the information inherent in the synthetic aperture is the same as that of an array with an equivalent physical aperture [17], [20].

Recent theoretical and experimental studies have addressed the above concerns and indicated that the space and time coherence of the acoustic signal in the sea [14], [15], [18], [22], [40], [41], [97] appears to be sufficient to extend the physical aperture of a moving line array. In the above studies, the fundamental question related to the angular resolution capabilities of a moving line array and the amount of information inherent in a received signal have been addressed. These investigations included the use of the CRLB analysis and showed that for long observation intervals on the order of 100 s, the additional information provided by a moving line array over a stationary array is expressed as a large increase in angular resolution, which is due to the Doppler caused by the movement of the array (see [17, Fig. 3]). A summary of these research efforts has been reported in a special issue of the IEEE JOURNAL OF OCEANIC ENGINEERING [14].

The synthetic-aperture processing scheme of the present development is based on the ETAM algorithm, which was invented by Stergiopoulos and Sullivan [16]. The basic concept of this algorithm is a phase-correction factor that is used to combine coherently successive measurements of the towed array to extend the effective towed array length.

Fig. 10 shows the experimental implementation of the ETAM algorithm in terms of the towed array positions as a function of time and space. Between two successive positions of the \( N \)-sensor line array with hydrophone spacing \( \delta \), there are \( (N - q) \) pairs of space samples of the acoustic field that have the same spatial information, their difference being a phase factor [17]–[20], [62] related to the time delay in which these measurements were taken. By cross correlating the \( (N - q) \) pairs of the hydrophone time series that overlap, the desired phase-correction factor is derived, which compensates for the time delay between these measurements and the phase fluctuations caused by irregularities of the tow path of the physical array; this is called the overlap correlator. Following the above, the key parameters in the ETAM algorithm are the time increment \( \tau = \delta/v \) between two successive sets of measurements, where \( v \) is the tow speed and \( q \) represents the number of hydrophone positions that the towed array has moved during \( \tau \) seconds or the number of hydrophones to which the physical aperture of the array is extended at each successive set of measurements. The optimum overlap size \( (N - q) \), which is related to the variance of the phase-correction estimates, has been shown [19] to be \( N/2 \). The total number of sets of measurements required to achieve a desired extended aperture size is then defined by \( J = (2/N)(Tv/d) \), where \( T \) is the period taken by the towed array to travel a distance equivalent to the desired length of the synthetic aperture.

Then for the frequency bin \( f_j \) and between two successive \( j \)th and \((j + 1)\)th snapshots, the phase-correction factor estimate is given by

\[
\hat{\psi}_j(f_i) = \arg\left\{ \frac{\sum_{n=1}^{N/2} X_{j,n}(f_i) \times X_{j,n+1}^*(f_i) \times \rho_{j,n}(f_i)}{\sum_{n=1}^{N/2} \rho_{j,n}(f_i)} \right\}
\]

(39)

where, for a frequency band with central frequency \( f_i \) and observation bandwidth \( \Delta f \) or \( f_i - \Delta f/2 < f_i < f_i + \Delta f/2 \), the coefficients

\[
\rho_{j,n}(f_i) = \sqrt{\sum_{i=-Q/2}^{Q/2} \frac{X_{j,(n/2+\alpha)}(f_i)}{X_{j,(n/2+\alpha)}^*(f_i)} \times \frac{X_{j,(n/2+\beta)}(f_i)}{X_{j,(n/2+\beta)}^*(f_i)}}
\]

(40)

are the normalized cross-correlation coefficients or the coherence estimates between the \( N/2 \) pairs of hydrophones that overlap in space. The above coefficients are used as weighting factors in (39) to optimally weight the good against the bad pairs of hydrophones during the estimation process of the phase-correction factor.

The performance characteristics and expectations from the ETAM algorithm have been evaluated experimentally,
Fig. 10. Concept of the experimental implementation of ETAM algorithm in terms of towed array positions as a function of time and space.

and the related results have been reported [17]–[20], [61], [62]. The main conclusion drawn from these experimental results is that for narrow-band signals or for frequency-modulated (FM) types of pulses from active sonar systems, the overlap correlator in ETAM compensates successfully the tow speed fluctuations and effectively extends the physical aperture of an array more than eight times. On the other hand, the threshold value of ETAM is $-8$ dB for a 1-Hz band at the sensor. For values of SNR higher than this threshold, it has been shown that ETAM achieves the theoretical CRLB bounds and has comparable performance to the maximum-likelihood estimator [17], [20].

IV. SYSTEM IMPLEMENTATION ASPECTS

A. Definition of a Generic Beam-Forming Structure for Sonar Systems

As stated in Section III-B, the major research effort of this project has been devoted to designing a generic beam-forming structure that will allow the implementation of adaptive, synthetic-aperture, and high-resolution temporal and spatial spectral analysis techniques in an integrated active–passive sonar system.

The practical implementation of the numerous adaptive and synthetic-aperture processing techniques, however, requires consideration of the characteristics of the signal and noise and the complexity of the ocean environment, as well as the computational difficulty. The discussion in Sections II and III addressed these concerns and prepared the ground for the development of the above generic beam-forming structure.

The major goal here in defining this generic signal-processing scheme is to exploit the great degree of processing concept similarities existing among the various types of processing techniques. Second is the definition of a computing architecture for the signal processor that will allow an effective implementation of the proposed signal-processing scheme. Third is the concept demonstration of both the technology and signal-processing concepts that is proving invaluable in reducing risk and in ensuring that significant innovations occur during the formal development process.

Fig. 11 shows the proposed configuration of the signal-processing flow that includes the implementation of FIR filters and conventional, adaptive, and synthetic-aperture beam formers. The reconfiguration of the different processing blocks in Fig. 11 allows the application of the proposed configuration into a variety of active and/or passive sonar systems. The shaded blocks in Fig. 11 represent advanced signal-processing concepts of next-generation sonar systems, and this basically differentiates their functionality from the current operational sonars.

The first point of the proposed processing flow configuration is that its implementation is in the frequency domain. The second point is that the frequency-domain beam-forming (or spatial filtering) outputs can be made equivalent to the FFT of the broad-band beam-former outputs with proper selection of beam-forming weights and careful data partitioning. This equivalence corresponds to implementing FIR filters via circular convolution. It also allows spatial-temporal processing of narrow- and broad-band-type signals as well. As a result, the output of each one of the processing blocks in Fig. 11 provides continuous time series. This modular structure in the signal-processing flow is a very essential processing arrangement in order to allow for the integration of a great variety of processing schemes such as those considered in this study.

The details of the proposed generic processing flow, as shown in Fig. 11, very briefly are the following.

- The block in this figure named “band formation” includes the partitioning of the time series from the receiving sensor array, their initial spectral FFT, the selection of the signal’s frequency band of interest via
bandpass FIR filters, and downsampling [65]–[67]. The output of this block provides continuous time series at reduced sampling rate.

- The major blocks, including “conventional” spatial fir filtering and “advanced beamformers” (adaptive and synthetic-aperture FIR filtering), provide continuous directional beam time series by using the FIR implementation scheme of the spatial filtering via circular convolution [64]–[67]. The segmentation and overlap of the time series at the input of the beam formers takes care of the wraparound errors that arise in fast-convolution signal-processing operations. The overlap size is equal to the effective FIR filter’s length.

- The block named “matched filter” is for the processing of echoes for active sonar applications. The intention here is to compensate also for the time-dispersive properties of the medium by having as an option the inclusion of the medium’s propagation characteristics in the replica of the active signal considered in the matched filter in order to improve detection and gain.

- The blocks “vernier,” “narrow-band spectral analysis,” and “broad-band spectral analysis” [67] include the final processing steps of a temporal spectral analysis. The inclusion of the vernier here is to allow the option for improved frequency resolution capabilities depending on the application.

- The block “display” includes the data normalization [42], [44] in order to map the output results into the dynamic range of the display devices in a manner that provides a CFAR capability.

The strength of this generic implementation scheme is that it permits under a parallel configuration the inclusion of nonlinear signal-processing methods, such as adaptive and synthetic aperture, as well as the equivalent conventional approach. This permits a very cost-effective evaluation of any type of improvements during the concept demonstration phase.

All the variations of adaptive processing techniques, while providing good bearing/frequency resolution, are sensitive to the presence of system errors. Thus, the deformation of a towed array, especially during course alterations, can be the source of serious performance degradation for the adaptive beam formers. This performance degradation is worse than that for the conventional beam former. So our concept of the generic beam-forming structure requires the integration of towed array shape estimation techniques [73]–[78] in order to minimize the influence of system errors on the adaptive beam formers. Furthermore, the fact that the advanced beam-forming blocks of this generic processing structure provide continuous-beam time series allows the integration of passive and active sonar application in one signal processor. Although this kind of integration may exist in conventional systems, the integration of adaptive and synthetic-aperture beam formers in one signal processor for active and passive applications has not been reported yet, except for the experimental system of this study, described in Section V. Thus, the beam time series from the output of the conventional and nonconventional beam formers are provided at the input of two different processing blocks, the passive and active processing units, as shown in Fig. 11.

In the passive unit, the use of verniers and the temporal spectral analysis (incorporating segment overlap, windowing, and FFT coherent processing [31], [32]), provide the narrow-band results for all the beam time series. Normalization and OR-ing [42], [44] are the final processing steps before displaying the output results. Since a beam time sequence can be treated as a signal from a directional hydrophone having the same array gain and directivity pattern as that of the above beam-forming processing schemes, the display of the narrow-band spectral estimates for all the beams follows the so-called LOFAR presentation arrangements, as shown in Figs. 15–17. This includes the display of the beam-power outputs as a function of time, steering beam (or bearing), and frequency. LOFAR displays are used mainly by sonar operators to detect and classify the narrow-band characteristics of a received signal.

Broad-band outputs in the passive unit are derived from the narrow-band spectral estimates of each beam by means of incoherent summation of all the frequency bins in a wide band of interest. This kind of energy content of the broad-band information is displayed as a function of bearing and time, as shown in Fig. 21.

In the active unit, the application of a matched filter (or replica correlator) on the beam time series provides coherent broad-band processing. This allows detection of
echoes as a function of range and bearing for reference wave forms transmitted by the active transducers of a sonar system. The displaying arrangements of the correlator’s output data are similar to the LOFAR displays and include, as parameters, range as a function of time and bearing, as shown in Fig. 24.

At this point, it is important to note that for active sonar applications, wave-form design and matched-filter processing must not only take into account the type of background interference encountered in the medium but should also consider the propagation characteristics (multipath and time dispersion) of the medium and the features of the target to be encountered in a particular underwater environment. Multipath and time dispersion in either deep or shallow water cause energy spreading that distorts the transmitted signals of an active sonar, and this results in a loss of matched filter processing gain if the replica has the properties of the original pulse [1]–[4], [8], [54], [102]. Results from a very recent study by Hermand and Roderick [103] have shown that the performance of a conventional matched filter can be improved if the reference signal (replica) compensates for the multipath and the time dispersion of the medium. This compensation is a model-based matched-filter operation, including the correlation of the received signal with the reference signal (replica) that consists of the transmitted signal convolved with the impulse response of the medium. Experimental results have shown also that the model-based matched-filter approach has improved performance with respect to the conventional matched-filter approach by as much as 3.6 dB. The above remarks should be considered as supporting arguments for the inclusion of model-based matched-filter processing in the generic signal-processing structure, shown in Fig. 11.

We focus our attention now on the processing arrangements for the adaptive subaperture schemes, which are summarized in Figs. 5–7 and 12. The subaperture processing scheme in Fig. 7 provides $S$ sets of beam time series, which are treated as $S$ arrays, each consisting of $J$ directional hydrophones with spacing $q$. Each set of $J$ directional hydrophone time series is provided at the input of the adaptive processor, which is illustrated in Figs. 5, 6, and 12. The mathematical details discussed in Section III-C and the appropriate indexes shown in these figures are self-explanatory in providing the details needed for mapping this computationally very intensive processing scheme in a scalar computing architecture. For adaptive beam formers, Fig. 12 summarizes their basic processing steps, which include:

1) time-series segmentation and overlap, shown by the block in the top right of the schematic diagram of Fig. 12;
2) FFT of segmented time series, formation of cross-covariance spectral density matrix, and its inversion using Cholesky factorization, presented by the middle and bottom blocks on the left-hand side of Fig. 12;
3) estimation of adaptive steering vectors and formation of adaptive beams in frequency domain, shown by the middle and bottom blocks in the middle part of Fig. 12;
4) formation of adaptive beams in time domain through IFFT, discarding of overlap, and concatenation of segments to form continuous-beam time series, shown in the left-hand block.

The indexes of Fig. 12 provide details for the implementation of the adaptive processing flow in a generic computing architecture.

For the synthetic-aperture processing scheme, however, there is an important detail regarding the segmentation and overlap of the hydrophone time series into sets of discontinuous segments. This segmentation process is associated with the tow speed and the size of the synthetic aperture, as discussed in Section III-F. So in order to achieve continuous data flow at the output of the overlap correlator, the $N$-continuous time series are segmented into discontinuous data sets, as shown in Fig. 13. Our implementation scheme in Fig. 13 considers five discontinuous segments in each data set. This arrangement will provide at the output of the overlap correlator $3N$-continuous hydrophone time series, which are provided at the input of the conventional beam former as if they were the hydrophone time series of an equivalent physical array. Thus, the basic processing steps include time-series segmentation, overlap, and grouping of five discontinuous segments, which are provided at the input of the overlap correlator, as shown by the group of blocks in the top part of Fig. 13. $\ell = M/f_s$ is the length in seconds of the discontinuous segmented time series and $M$ defines the size of FFT. The rest of the blocks provide the indexing details for the formation of the synthetic aperture. These indexes also provide details for the implementation of the segmentation process of the synthetic-aperture processing flow in a generic computing architecture.

The processing arrangements and the indexes in Fig. 14 provide the details needed for the mapping of this synthetic-aperture processing scheme in a sonar computing architecture. The basic processing steps include the following.

1) Time series segmentation, overlap, and grouping of five discontinuous segments, which are provided at the input of the overlap correlator, shown by the block in the top part of schematic diagram. Details of this segmentation process are shown also in Fig. 13.
2) The main block, “ETAM: overlap correlator,” provides processing details for the estimation of the phase-correction factor to form the synthetic aperture (39) and (40).
3) Formation of the continuous sensor time series of the synthetic aperture are obtained through IFFT, discarding of overlap, and concatenation of segments to form continuous time series, shown in the left-hand block.

It is important to note here that the choice of five discontinuous segments was based on experimental observations [18] regarding the temporal and spatial coherence properties
Fig. 12. Schematic diagram for the processing details of adaptive beam formers. The basic processing steps include: 1) time-series segmentation and overlap (block at the top right of schematic diagram); 2) FFT of segmented time series, formation of cross-covariance spectral density matrix, and its inversion using Cholesky factorization (middle and bottom blocks on the left-hand side); 3) estimation of adaptive steering vectors and formation of adaptive beams in frequency domain (middle and bottom blocks in the middle part of schematic diagram); and 4) formation of adaptive beams in time domain through IFFT, discarding of overlap, and concatenation of segments to form continuous beam time series (left-hand block). The various indexes provide details for the implementation of the adaptive processing flow in a generic computing architecture.

of the underwater medium. These issues of coherence are very critical for synthetic-aperture processing and have been addressed in Section III-B.

B. Comments on Computing Architecture Requirements

The implementation of this investigation’s unconventional processing schemes in sonar and radar systems is a nontrivial issue. In addition to the selection of the appropriate algorithms, success is heavily dependent on the availability of suitable computing architectures.

Past attempts to implement matrix-based signal-processing methods, such as adaptive beam formers reported in this paper, were based on the development of systolic array hardware because systolic arrays allow large amounts of parallel computation to be performed efficiently since communications occur locally. None of these ideas is new. Unfortunately, systolic arrays have been much less successful in practice than in theory. The fixed-size problem for which it makes sense to build a specific array is rare. Systolic arrays big enough for real problems cannot fit on one board, much less one chip, and interconnects have problems. A 2-D systolic array implementation will be even more difficult. So any new computing architecture development should provide high throughput for vector-as well as matrix-based processing schemes.

A fundamental question, however, that must be addressed at this point is whether it is worthwhile to attempt to develop a system architecture that can compete with a multiprocessor using stock microprocessors. Although recent microprocessors use advanced architectures, improvement of their performance includes a heavy cost in design complexity, which grows dramatically with the number of instructions that can be executed concurrently. Moreover, the recent microprocessors, which claim high performance for peak rates of millions of floating operations per second, have their net throughput usually much lower, and their memory architectures are targeted toward general-purpose code.

The above issues establish the requirement for dedicated architectures, such as in the area of operational sonar systems. Sonar applications are computationally intensive, as shown in Section IV of this paper, and they require
Fig. 13. Schematic diagram of the data flow for the ETAM algorithm and the sensor time-series segmentation into a set of five discontinuous segments for the overlap correlator. The basic processing steps include time-series segmentation, overlap, and grouping of five discontinuous segments, which are provided at the input of the overlap correlator (shown by the group of blocks in the top part of schematic diagram). \( T = \frac{M}{f_s} \) is the length in seconds of the discontinuous segmented time series and \( M \) defines the size of FFT. The rest of the blocks provide the indexing details for the formation of the synthetic aperture. These indexes provide details for the implementation of the segmentation process of the synthetic-aperture flow in a generic computing architecture. The processing flow is shown in Fig. 14.

High throughput on large data sets. It is our understanding that the Canadian Department of National Defence recently supported work for a new sonar computing architecture called the next-generation signal processor (NGSP) [10]. We believe that the NGSP has established the hardware configuration to provide the required processing power for the implementation and real-time testing of nonconventional beam formers such as those reported in this paper.

A detailed discussion about the NGSP, however, is beyond the scope of this paper. A brief overview of this new signal processor can be found in [10]. Other advanced computing architectures that can cover the throughput requirements of computationally intensive signal-processing applications, such as those discussed in this manuscript, have been developed by Mercury Computer Systems [104]. Based on the experience of the author, the suggestion is that implementation efforts of advanced signal-processing concepts should be directed more toward the development of generic signal-processing structures as in Fig. 11 rather than toward the development of very expensive computing architectures. Moreover, the signal-processing flow of advanced processing schemes that include both scalar and vector operations should be very well defined in order to address practical implementation issues.

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In this paper, we have addressed the issue of computing architecture requirements by defining generic concepts of the signal-processing flow for integrated active–passive sonar systems, including adaptive and synthetic-aperture signal-processing schemes. The schematic diagrams in Figs. 6, 7, and 11–13 that show the signal-processing flow of the advanced processing concepts of this study provide a realistic effort in that regard. Their implementation can be carried out in existing computer architectures [10], [104] as well as in a network of general-purpose computer workstations that support both scalar and vector operations.

V. CONCEPT DEMONSTRATION: EXPERIMENTAL RESULTS

The real data sets that have been used in this study to test the implementation configuration of the above non-conventional processing schemes come from two kinds of experimental setups. The first one included sets of experimental data representing an acoustic field consisting of the tow ship’s self-noise and the reference narrow-band CW’s, as well as broad-band signals such as hyperbolic frequency-modulated (HFM) and pseudo-random transmitted waveforms from a deployed source. The absence of other noise sources as well as noise from distant shipping during these experiments make this set of experimental data very appropriate for concept demonstration. This is because there are only a few known signals in the received hydrophone time series, and this allows an effective testing of the performance of the above generic signal-processing structure by examining various possibilities of artifacts that could be generated by the nonconventional beam formers.
In the second experimental setup, the received hydrophone data represent an acoustic field consisting of the reference CW, HFM, and broad-band signals from the deployed source that are embodied in a highly correlated acoustic noise field, including narrow- and broad-band noise from heavy shipping traffic. During the experiments, signal conditioning and continuous recording on a high-performance digital recorder was provided by a real-time data system.

The generic signal-processing structure, presented in Fig. 11, and the associated signal-processing algorithms (MVDR, GSC, STMV, ETAM, matched filter) were implemented in a workstation supporting a UNIX operating system and FORTRAN and C compilers, respectively.

Although the CPU power of the workstation was not sufficient for real-time signal-processing response, the memory of the workstation supporting the signal-processing structure of Fig. 11 was sufficient to allow processing of continuous hydrophone time series up to three hours long. Thus, the output results of the above generic signal-processing structure were equivalent to those that would have been provided by a real-time system including the implementation of the signal-processing schemes discussed in this paper.

The results presented in this section are divided into two parts. The first part discusses passive narrow- and broad-band towed array sonar applications. The scope here is to evaluate the performance of the adaptive and synthetic-aperture beam-forming techniques and to assess their ability to track and localize narrow- and broad-band signals of interest while suppressing strong interferers. The impact and merits of these techniques will be contrasted with the localization and tracking performance obtained using the conventional beam former.

The second part of this section presents results from active towed array sonar applications. The aim here is to evaluate the performance of the adaptive and synthetic-aperture beam formers in a matched-filter processing environment.

A. Passive Towed Array Sonar Applications

1) Narrow-Band Acoustic Signals: The display of narrow-band bearing estimates according to a LOFAR presentation arrangement is shown in Figs. 15–17. Twenty-five beams equally spaced in [1, −1] cosine space were steered for the conventional, adaptive, and synthetic-aperture beam-forming processes. The wavelength $\lambda$ of
Fig. 16. Synthetic-aperture (ETAM algorithm) LOFAR narrow-band output. The processed sensor time series are the same as those of Fig. 15. The basic difference between the LOFAR-gram results of the conventional beam former in Fig. 15 and those of the synthetic-aperture beam former is that the improved directionality (array gain) of the nonconventional beam former localizes the detected narrow-band signals in a smaller number of beams than the conventional beam former. For the synthetic-aperture beam former, this is translated into a better tracking and localization performance for detected narrow-band signals, as shown in Figs. 18 and 19.

The reference CW signal was approximately equal to $1/6$ of the aperture size $L$ of the deployed line array. The power level of the above CW signal was in the range of 130 dB for 1 $\mu$Pa, and the distance between the source and the receiver was on the order of $O(10^3)$ nm. The water depth in the experimental area was 1000 m and the deployment depths of the source and the array receiver were approximately 100 m.

Fig. 15 presents the conventional beam former’s LOFAR output. At this particular moment, we started to lose detection of the above reference CW signal tonal. Very weak indications of the presence of this CW signal are shown in beams 21–24 of Fig. 15. In Figs. 16 and 17, the LOFAR outputs of the synthetic aperture and the partially adaptive subaperture MVDR processing schemes are shown for the set of data and are the same as those of Fig. 15. In particular, Fig. 16 shows the synthetic-aperture (ETAM algorithm) LOFAR narrow-band output, which indicates that the basic difference between the LOFAR-gram results of the conventional beam former in Fig. 15 and those of the synthetic-aperture beam former is that the improved directionality (array gain) of the nonconventional beam former localizes the detected narrow-band signals in a smaller number of beams than the conventional beam former. For the synthetic-aperture beam former, this is translated into a better tracking and localization performance for detected narrow-band signals, as shown in Figs. 18 and 19.

Fig. 17 presents the subaperture MVDR beam former’s LOFAR narrow-band output. In this case, the processed sensor time series are the same as those of Figs. 15 and 16. However, the sharpness of the adaptive beam former’s LOFAR output was not as good as that of the conventional and synthetic-aperture beam former. This indicated loss of temporal coherence in the adaptive beam time series, which was caused by nonoptimum performance and poor convergence of the adaptive algorithm. The end result was poor tracking of detected narrow-band signals by the adaptive schemes, as shown in Fig. 20.

The narrow-band LOFAR results from the subaperture GSC and STMV adaptive schemes were almost identical with those of the subaperture MVDR scheme, shown in Fig. 17. For the adaptive beam formers, the number of itera-
Subaperture MVDR beam former’s LOFAR narrow-band output. The processed sensor time series are the same as those of Figs. 15 and 16. Even though the angular resolution performance of the subaperture MVDR scheme in this case was better than that of the conventional beam former, the sharpness of the adaptive beam former’s LOFAR output was not as good as that of the conventional and synthetic-aperture beam former. This indicated loss of temporal coherence in the adaptive beam time series, which was caused by nonoptimum performance and poor convergence of the adaptive algorithm. The end result was poor tracking of detected narrow-band signals by the adaptive schemes, as shown in Fig. 20.

Loss of coherence is evident in the LOFAR outputs because the generic beam-forming structure in Fig. 11 includes coherent temporal spectral analysis of the continuous-beam time series for narrow-band analysis. For the adaptive schemes implemented in element space, the number of iterations for the adaptive exponential averaging of the sample covariance matrix was 200 snapshots, \( \mu = 0.9 \) according to (38). In particular, the MVDR element space method required a very long convergence period on the order of 3000 s. In cases where this convergence period was reduced, the MVDR element space LOFAR output was populated with artifacts [23]. However, the performance of the adaptive schemes of this study (MVDR, GSC, STMV) improved significantly when their implementation was carried out under the subaperture configuration, shown in Fig. 7.

Apart from the presence of the CW signal with \( \lambda = L/6 \) in the conventional LOFAR display, only two more
The narrow-band beam-power maps of the LOFAR-grams in Figs. 15–17 form the basic unit of acoustic information that is provided at the input of the data manager of our system for further information extraction. As discussed in Section I-C, one basic function of the data-management algorithms is to estimate the characteristics of signals that have been detected by the beam-forming and spectral-analysis processing schemes, which are shown in Fig. 11. The data-management processing includes signal following or tracking [105], [106] that provides monitoring of the time evolution of the frequency and the associated bearing of detected narrow-band signals.

If the output results from the nonconventional beam formers exhibit improved array-gain characteristics, this kind of improvement should deliver better system tracking performance over that of the conventional beam former. To investigate the tracking performance improvements of the synthetic-aperture and adaptive beam formers, the deployed source was towed along a straight line course while the towing of the line array receiver included a few course alterations over a period of approximately three hours. Fig. 19 illustrates this scenario, showing the constant course of the towed source and the course alterations of the vessel towing the line array receiver.

The parameter estimation process for tracking the bearing of detected sources consisted of peak picking in a region of bearing and frequency space sketched by fixed gate sizes in the LOFAR-gram outputs of the conventional and nonconventional beam formers. Details about this estimation process can be found in [107]. Briefly, the choice of the gate sizes was based on the observed bearing and frequency fluctuations of a detected signal of interest during the experiments. Parabolic interpolation was used to provide refined bearing estimates [108]. For this investigation, the bearing-only tracking process described in [107] was used as a narrow-band tracker, providing unsmoothed time evolution of the bearing estimates to the localization process [105], [109]. The localization process of this study was based on a recursive extended Kalman filter formulated in Cartesian coordinates. Details about this localization process can be found in [107] and [109].

The solid line in Fig. 18 shows the expected bearings of a detected CW signal with respect to the towed array receiver. The dots in the same figure represent the tracking results of bearing estimates from LOFAR data provided by the synthetic-aperture and conventional beam formers. The middle part of Fig. 18 illustrates the tracking results of the synthetic-aperture beam former. In this case, the wavelength $\lambda$ of the narrow-band CW signal was approximately equal to $1/3$ of the aperture size of the deployed towed array (DI narrow-band signals with wavelengths approximately equal to $\lambda = L/3$ were detected. No other signals were expected to be present in the acoustic field, and this is confirmed by the conventional narrow-band output of Fig. 15, which has white-noise characteristics. This kind of simplicity in the received data is essential for this kind of demonstration process in order to identify the presence of artifacts that could be produced by the various beam formers.

Fig. 18. Signal following of bearing estimates from the conventional beam-forming LOFAR narrow-band outputs and the synthetic aperture (ETAM algorithm). Solid line shows the true values of source’s bearing. The wavelength of the detected CW was equal to $1/3$ of the aperture size $L$ of the deployed array. For reference, the tracking of bearing from conventional beam-forming LOFAR outputs of another CW with wavelength equal to $1/16$ of the towed array’s aperture is shown in the lower part.
Fig. 19. (a) Signal following of bearing estimates from conventional beam-forming and synthetic-aperture (ETAM algorithm) LOFAR narrow-band outputs. Solid line shows the true values of source's bearing. (b) Localization estimates that were based on the bearing tracking results shown in (a).

For this very low frequency CW signal, the tracking performance of the conventional beam former was very poor, as shown by the upper part of Fig. 18. To provide a reference, the tracking performance of the conventional beam former for a CW signal, having wavelength approximately equal to 1/16 of the aperture size of the deployed array (DI = 7.6 dB), is shown in the lower part of Fig. 18.

Localization estimates for the acoustic source transmitting the CW signal with $\lambda = L/3$ were derived only from the synthetic-aperture tracking results, shown in the middle of Fig. 18. In contrast to these results, the conventional beam former's localization estimates did not converge because the variance of the associated bearing tracking results was very large, as indicated by the results of the upper part of Fig. 18. As expected, the conventional beam former's localization estimates for the higher frequency CW signal $\lambda = L/16$ converge to the expected solution. This is because the system array gain in this case was higher (DI = 15 dB), resulting in better bearing tracking performance with a very small variance in the bearing estimates.
The tracking and localization performance of the synthetic-aperture and conventional beam-forming techniques was also assessed from other sets of experimental data. In this case, the towing of the line array receiver included only one course alteration over a period of approximately 30 min. Fig. 19 presents a summary of the tracking and localization results from this experiment. Fig. 19(a) shows tracking of the bearing estimates provided by the synthetic-aperture and conventional beam-forming LOFAR-gram outputs. Fig. 19(b) presents the localization estimates derived from the corresponding tracking results.

It is apparent from the results of Figs. 18 and 19 that the synthetic-aperture beam former improves the array gain of small-size array receivers, and this improvement is translated into a better signal-tracking and target-localization performance than the conventional beam former.

With respect to the tracking performance of the narrowband adaptive beam formers, our experience is that during course alterations, the tracking of bearings from the narrowband adaptive beam-power outputs was very poor. As an example, Fig. 20(b) shows the subaperture MVDR adaptive beam former’s bearing tracking results for the same set of data as in Fig. 19. It is clear in this case that the changes of the towed array’s heading are highly correlated with the deviations of the adaptive beam former’s bearing tracking results from their expected estimates.

Although the angular resolution performance of the adaptive beam former was better than that of the synthetic-aperture processing, the lack of sharpness and the fuzziness and discontinuity in the adaptive LOFAR-gram outputs prevented the signal following algorithms from tracking the signal of interest [107]. Thus, the subaperture adaptive algorithm should have provided better bearing estimates than those indicated by the output of the bearing tracker, shown in Fig. 20. To address this point, we plotted the subaperture MVDR bearing estimates as a function of time for all the 25 steered beams equally spaced in [1, -1] cosine space for a frequency bin including the signal of interest. Fig. 20(a) shows a waterfall of these bearing estimates. It is apparent in this case that our bearing tracker failed to follow the narrow-band bearing outputs of the adaptive beam former. Moreover, the results in Fig. 20(a) suggest signal fading and performance degradation for the narrow-band adaptive processing during certain periods of the experiment.

Our explanation for this performance degradation is twofold. First, the drastic changes in the noise field, due to a course alteration, would require a large number of iterations for the adaptive process to converge. Second, since the associated sensor coordinates of the towed array shape deformation had not been considered in the steering vector $\mathbf{D}(f_i, \theta)$ in (23), (27), and (35), this omission induced erroneous estimates in the noise covariance matrix during the iteration process of the adaptive processing. If a towed array shape estimation algorithm had been included in this case, the adaptive process would have provided better bearing tracking results than those shown in Fig. 20 [77], [107]. For the broad-band adaptive results, however, the situation is completely different, and this is addressed in the following section.

2) Broad-Band Acoustic Signals: Fig. 21 shows the conventional and subaperture adaptive broad-band bearing estimates as a function of time for a set of data representing an acoustic field consisting of radiated noise from distant shipping in acoustic conditions typical of a sea state two to four. The experimental area here is different than that including the processed data presented in Figs. 15–20. The processed frequency regime for the broad-band bearing estimation was the same for both the conventional and partially adaptive subaperture MVDR, GSC, and STMV processing schemes. Since the beam-forming operations in this study are carried out in frequency domain, the low-frequency resolution in this case was on the order of $O(10^6)$. That resulted in very short convergence periods for
Fig. 21. Broad-band bearing estimates for a two-hour-long set of data. (a) Output from conventional beam former. (b) Output from subaperture MVDR beam former. Solid red lines show signal tracking results for the broad-band bearing estimates provided by the conventional and subaperture MVDR beam formers. These results show a superior signal detection and tracking performance for the broad-band adaptive scheme compared with that of the conventional beam former. This performance difference was consistent for a wide variety of real data sets.

It is evident by these results that the subaperture adaptive schemes of this study provide better detection (than the conventional beam former) of weak signals in the presence of strong signals. For the above set of data, shown in Fig. 21, broad-band bearing tracking results (for a few broad-band signals at bearing 245°, 265°, and 285°) are shown by the red solid lines for both the adaptive and conventional broad-band outputs. As expected, the signal followers of the conventional beam former lost track of the broad-band signal with bearing 240° at the time position (240°, 6300 s). On the other hand, the trackers of the subaperture adaptive beam formers did not lose track of this target, as shown by the results in Fig. 21(b). At this point, it is important to note that the broad-band outputs of...
the subaperture MVDR, GSC, and STMV adaptive schemes were almost identical.

It is apparent from these results that the partially adaptive subaperture beam formers have better performance than the conventional beam former in detecting very weak signals. In addition, the subaperture adaptive configuration has demonstrated equivalence to the conventional beam former’s dynamic response in tracking targets during the tow vessel’s course alterations. For the above set of data, localization estimates based on the broad-band bearing tracking results of Fig. 21 converged to the expected solution for both the conventional and adaptive processing beam outputs.

Given the fact that the broad-band adaptive beam former exhibits better detection performance than the conventional method—as shown by the results of Fig. 21 and other data sets, which are not reported here—it is concluded that for broad-band signals, the subaperture adaptive beam formers of this study provide significant improvements in array gain that result in better tracking and localization performance than that of the conventional signal-processing scheme.

At this point, questions may be raised about the differences in bearing tracking performance of the adaptive beam former for narrow- and broad-band applications. It appears that the broad-band subaperture adaptive beam formers as energy detectors exhibit very robust performance because the incoherent summation of the beam powers for all the frequency bins in a wide band of interest removes the fuzziness of the narrow-band adaptive LOFAR-gram outputs, shown in Fig. 17. However, a signal follower capable of tracking fuzzy narrow-band signals [27] in LOFAR-gram outputs should remedy the observed instability in bearing trackings for the adaptive narrow-band beam outputs. In addition, towed array shape estimators should also be included because the convergence period of the narrow-band adaptive processing is of the same order as the period associated with the course alterations of the towed array operations. None of these remedies is required for broad-band adaptive beam formers because of their proven robust performance as energy detectors and the short convergence periods of the adaptation process during course alterations.

### B. Active Towed Array Sonar Applications

It was discussed in Section IV-A that the configuration of the generic beam-forming structure to provide continuous-beam time series at the input of a matched filter and a temporal spectral analysis unit forms the basis for integrated passive and active sonar applications. Before the adaptive and synthetic-aperture processing schemes are integrated with a matched filter, however, it is essential to demonstrate that the beam time series from the output of these nonconventional beam formers have sufficient temporal coherence and correlate with the reference signal. For example, if the received signal by a sonar array consists of FM-type pulses with a repetition rate of a few minutes, then questions may be raised about the efficiency of an adaptive beam former to achieve near instantaneous convergence in order to provide beam time series with coherent content for the FM pulses. This is because partially adaptive processing schemes require at least a few iterations to converge to a suboptimum solution.

To address this question, the matched filter and the nonconventional processing schemes, shown in Fig. 11, were tested with real data sets, including HFM pulses 8 s long with 100 Hz bandwidth. The repetition rate was 120 s. Although this may be considered as a configuration for bistatic active sonar applications, the findings from this experiment can be applied to monostatic active sonar systems as well.

Figs. 22 and 23 present some experimental results from the output of the active unit of the generic signal-processing structure. Fig. 22 shows the output of the replica correlator for the conventional, subaperture MVDR adaptive, and synthetic-aperture beam time series. The horizontal axis in this figure represents range or time delay of 0–120 s, which is the repetition rate of the HFM pulses. While the three beam-forming schemes provide artifact-free outputs, it is apparent from the values of the replica correlator output that the conventional beam time series exhibit better temporal coherence properties than the beam time series of the synthetic-aperture and subaperture adaptive beam former. The significance and a quantitative estimate of this difference can be assessed by comparing the amplitudes of the normalized correlation outputs in Fig. 22. In this case, the amplitudes of the replica correlator outputs are 0.32, 0.28, and 0.29 for the conventional, adaptive, and synthetic-aperture beam formers, respectively.

This difference in performance, however, was expected because for the synthetic-aperture processing scheme to achieve optimum performance, the reference signal is required to be present in the five discontinuous snapshots that are being used by the overlapped correlator to synthesize the synthetic aperture. So if a sequence of five HFM pulses had been transmitted with a repetition rate equal to the time interval between the above discontinuous snapshots, then the coherence of the synthetic-aperture beam time series would have been equivalent to that of the conventional beam former. Normally, this kind of requirement restricts the detection ranges for incoming echoes. To overcome this limitation, a combination of the pulse length, desired synthetic-aperture size, and detection ranges should be derived that will be based on the aperture size of the deployed array. A simple application scenario, illustrating the concept of this combination, is a side-scan sonar system that deals with predefined ranges.

Although for the adaptive beam time series in Fig. 22 a suboptimum convergence was achieved within two to three iterations, the arrangement of the transmitted HFM pulses in this experiment was not an optimum configuration because the subaperture beam former had to achieve near instantaneous convergence with a single snapshot. Our simulations suggest that a suboptimum solution for the subaperture MVDR adaptive beam former is possible if the active sonar transmission consists of a continuous sequence of active pulses. In this case, the number of pulses in a sequence should be a function of the number of
subapertures of Fig. 7, and the repetition rate of this group of pulses should be a function of the detection ranges of operational interest.

The near instantaneous convergence characteristics for the other two adaptive beam formers, however, namely the GSC and the STMV schemes, are better compared with those of the subaperture MVDR scheme. Fig. 23 shows the replica correlator output for the same set of data as in Fig. 22 and for the beam series of the conventional and subaperture MVDR, GSC, and STMV adaptive schemes.

Even though the beam-forming schemes of this study provide artifact-free outputs, it is apparent from the values of the replica correlator outputs, shown in Figs. 22 and 23, that the conventional beam time series exhibit better temporal coherence properties than the beam time series of the adaptive beam formers, except for the subaperture STMV scheme. The significance and a quantitative estimate of this difference can be assessed by comparing the amplitudes of the correlation outputs in Fig. 23. In this case, the amplitudes of the replica correlator outputs are 10.51, 9.65, 9.01, 10.58 for the conventional and adaptive schemes (GSC in element space, GSC-SA, and STMV-SA), respectively. These results show that the beam time series of the STMV subaperture scheme have achieved temporal coherence properties equivalent to those of the conventional beam former, which is the optimum case.

Normalization and OR-ing of matched filter outputs, such as those of Figs. 22 and 23, and their display in a LOFAR-gram arrangement would provide a waterfall display of ranges as a function of beam steering and time. Fig. 24 shows these results for the correlation outputs of the conventional and adaptive beam time series for beam 23. It should be noted that this figure includes approximately two hours of processed data. The detected HFM pulses and
Fig. 24. Waterfall display of replica correlator outputs as a function of time for the same conventional and adaptive beam time series as those of Fig. 23. It should be noted that this figure includes approximately two hours of processed data. The detected HFM pulses and their associated ranges are clearly shown in beam 23. A reflection from the side walls of an underwater canyon in the area is visible as a second echo closely spaced with the main arrival.

their associated ranges are clearly shown in beam 23. A reflection from the side walls of an underwater canyon in the area is visible as a second echo closely spaced with the main arrival.

In summary, the basic difference between the LOFAR-gram results of the adaptive schemes and those of the conventional beam time series is that the improved directionality of the nonconventional beam formers localizes the detected HFM pulses in a smaller number of beams than the conventional beam former. Although we do not present here the LOFAR-gram correlation outputs for all the 25 beams, a picture displaying the 25 beam outputs would confirm the above statement regarding the directionality improvements of the adaptive schemes with respect to the conventional beam former. Moreover, it is anticipated that the directional properties of the nonconventional beam formers would suppress the anticipated reverberation levels during active sonar operations. Thus, if there are going to be advantages regarding the implementation of the above nonconventional beam formers in active sonar applications, it is expected that these advantages would include minimization of the impact of reverberations by means of improved directionality. More specifically, the improved directionality of the nonconventional beam formers would restrict the reverberation effects of active sonars in a smaller number of beams than that of the conventional beam former. This improved directionality would enhance the performance of an active sonar system (including nonconventional beam formers) to detect echoes located near the beams that are populated with reverberation effects.

VI. CONCLUSION

The experimental results of this study were derived from a wide variety of CW, broad-band, and HFM-type strong and weak acoustic signals. The fact that adaptive and synthetic-aperture beam formers provided improved detection and tracking performance (Figs. 15–22), for the above type of signals and under a real-time data flow as the conventional beam former, demonstrates the merits of these nonconventional processing schemes for sonar applications. In addition, the generic implementation scheme of this study suggests that the design approach to provide synergism between the conventional beam former and the adaptive and synthetic-aperture processing schemes could probably provide some answers to the integrated active and passive sonar problem in the near future.

Although the focus of the implementation effort included only adaptive and synthetic-aperture processing schemes, the consideration of other types of nonlinear processing schemes for real-time sonar and radar applications should not be excluded. The objective here was to demonstrate that nonconventional processing schemes can address some of the challenges that the next-generation active–passive sonars as well as radar systems will have to deal with in the near future. Once a computing architecture and a generic signal-processing structure are established, such as those suggested in this paper, the implementation of a wide variety of nonlinear processing schemes in real-time sonar and radar systems can be achieved with minimum effort.

In conclusion, the above results suggest that the broad-band outputs of the subaperture adaptive processing schemes (Fig. 21) and the narrow-band synthetic-aperture LOFAR-grams (Fig. 16) exhibit very robust performance (under the prevailing experimental conditions) and that their array-gain improvements provide better signal-tracking and target-localization estimates (Figs. 18, 19, and 21) than the conventional processing schemes. It is worth noting also that the reported improvements in performance of the above nonconventional beam formers compared with that of the conventional beam former have been consistent for a wide variety of real data sets. For the implementation configuration of the adaptive schemes in element space, however, the narrow-band adaptive implementation requires very long convergence periods, which makes the application of the adaptive processing schemes in element impractical. This is because the associated long convergence periods destroy the dynamic response of the beam-forming process, which is very essential during course alterations and for cases that include targets with dynamic changes in their bearings.

Last, the experimental results of this study indicate that the subaperture GSC and STMV adaptive schemes address the practical concerns of near instantaneous convergence associated with the implementation of adaptive beam formers in integrated active–passive sonar systems.
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