Advances in Information Processing in Oceans Technology
A 40 Year Review

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Abstract - **Raw data can be filtered, aggregated, transformed, fused, visualized, and correlated, yet data by itself is of no practical value. For data to be of value it must first be interpreted. Interpretation/analysis is a necessary but insufficient condition for conveying information. The interpretation must impact the behavior of the end user for the data to be truly useful, hence the term actionable intelligence. This forms the underlying basis of all information processing systems: utilize data collected from a variety of sources to piece together a view of the world that enables an end user to make enlightened decisions with respect to this environment. Information processing (IP) systems take various forms, many of which combine technology from several scientific fields. Within the past four decades we have seen IP systems incorporate many technological advances including Bayesian Networks, multi-hypothesis data fusion, expert systems, artificial neural networks (ANNs), fuzzy systems, and evolutionary algorithms. The ocean sciences have benefited significantly from these technologies as they have provided new solutions to difficult and previously (computationally) intractable problems. This paper highlights some of the major advances in information processing and data fusion efforts in oceans technology over the past four decades, and presents some predictions about future developments in this dynamically changing arena.**

I. INTRODUCTION

Information/Data processing technologies encompass and overlap a wide variety of areas. Data fusion, parameter estimation, signal/image processing, pattern recognition, inference generation, and position tracking are but a few of the technologies under this wide umbrella. In the past four decades, a plethora of advances in mathematical and computational techniques, as well as computer processing capabilities have been made that have both directly and indirectly benefited the ocean sciences. A look through the proceedings of the OCEANS/MTS conference from its inception in 1970 (as the IEEE Conference on Engineering in the Ocean Environment) through this year's OCEANS' 08 conference reveals several notable technological breakthroughs that have had major and long lasting impacts. The following areas have been selected as particularly important advances for our OCEANS community with respect to information processing technologies.

II. THE KALMAN FILTER

Data and information processing methods involving random variables is known as estimation theory. Since Gauss (circa 1800) [1] derived the well-known method of 'least-squares' there have been numerous advances in this important field. While a number of major contributions to this theory have been made since [2],[3],[4], most were principally limited to steady-state, statistically stationary processes. Though Wiener [5] extended the theory to include non-stationary processes, it wasn't until the early 1960s when Kalman [6], [7] (among others) developed a recursive, optimal filtering technique based on state-space, time-domain formulations. This presented a major breakthrough as this new recursive approach was ideally suited to implementation on a computer whereas the previous techniques proved cumbersome, at best. The iterative formulation of this optimal filter reduced memory storage requirements which were a significant factor at the time. The basic equations of the (extended) Kalman filter are defined in Fig 1.

$$\boldsymbol{x}'_k = \boldsymbol{x}_{k/k-1} = \varphi_k\ \boldsymbol{x}_{k/k-1} \tag{1}$$
$$\boldsymbol{P}'_k = \boldsymbol{P}_{k/k-1} = \varphi_k\ \boldsymbol{P}_{k-1/k-1}\ \varphi_k^{\mathrm{T}} + \boldsymbol{Q}_k \tag{2}$$
$$\boldsymbol{K}_k = \boldsymbol{P}'_k\ \boldsymbol{H}_k\ (\boldsymbol{H}_k\ \boldsymbol{P}'_k\ \boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k)^{-1} \tag{3}$$
$$\boldsymbol{xr}_k = \boldsymbol{z}_k - \boldsymbol{H}_k\ \boldsymbol{x}'_k \tag{4}$$
$$\boldsymbol{x}_{k/k} = \boldsymbol{x}'_k + \boldsymbol{K}_k\ \boldsymbol{xr}_k \tag{5}$$
$$\boldsymbol{P}_{k/k} = (\mathbf{I} - \boldsymbol{K}_k\ \boldsymbol{H}_k)\ \boldsymbol{P}'_k \tag{6}$$

or in it's alternative symmetric formulation

$$\boldsymbol{P}_{k/k} = (\mathbf{I} - \boldsymbol{K}_k\ \boldsymbol{H}_k)\ \boldsymbol{P}'_k(\mathrm{I} - \boldsymbol{K}_k\ \boldsymbol{H}_k)^{\mathrm{T}} + \boldsymbol{K}_k\boldsymbol{R}_k\boldsymbol{K}_k^{\mathrm{T}} \tag{7}$$

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where

$\boldsymbol{x}_{k/k}$ = the state estimate vector
$\boldsymbol{P}_{k/k}$= the error covariance matrix
$\boldsymbol{z}_k$ = the measurement vector
$\boldsymbol{H}_k$ = the measurement matrix
$\boldsymbol{R}_k$ = the measurement noise covariance matrix
$\boldsymbol{K}_k$ = the Kalman gain matrix
$\boldsymbol{P}'_k$ = the prediction error covariance matrix
$\boldsymbol{x}'_k$ = the state estimate vector
$\boldsymbol{Q}_k$ = the system dynamics noise matrix
φ_k = the system dynamics noise matrix
$\mathbf{I}$ = the identity matrix

Figure 1. (Extended) Kalman filter equations.

The ocean sciences pose numerous opportunities for applied estimation theory, ranging from tracking objects, positions and state estimates to navigation and heave compensation. One of the first applications of the Kalman filter in the ocean sciences can be found in the work of Lee [8]. Lee developed a Kalman filter to create a best-estimate of the vehicle position in an acoustic transponder system. This research demonstrated the filter's stability using a simulated 3-transponder system, as well as its suitability to track surface and undersea vehicles. That same year Aidala and Davis [9] investigated the use of a modified performance index to control error divergence. Their paper demonstrated the use of this index to adaptively regulate the plant noise covariance matrix as an effective mechanism for reducing error divergence.

In 1974 Timchenko applied Kalman filters to estimate the depth of ocean isothermal layers, to predict the vertical distribution of temperature, and current velocity vectors [10]. A few years later Carta [11] proposed a new approach to the problem of locating the relative positions of transponders using Kalman's optimal estimation theory. Carta's research applied optimal filtering techniques together with the principles of multilateration of line crossing measurements, and demonstrated how accurate position estimates could be obtained without requiring data collected at regularly spaced (i.e., Cartesian grid) points.

Grimble, et al [12] investigated and compared the performance of a Balchen extended Kalman filter (EKF) to the traditional filter representation on the ship-positioning problem using an 18-state model. They proposed an alternative formulation based on the direct modeling of wave energy spectra. Although there were some disadvantages of the proposed technique, the new method's filter gains proved non-oscillatory and settled to constant mean values. The convergence of the high-frequency model parameters was quite rapid with the state estimates approaching the Pierson-Moskowitz spectrum in a least-squares sense.

Kalman filters have also been applied to navigation, control and parameter identification of undersea vehicles [13]. Ozimina and Bierman employed EKFs for near real-time parameter identification in a parameter-adaptive control structure. Classical methods of guidance and control were contrasted with the new techniques for control of ballast, trim, speed, and depth/pitch. Their controller simultaneously identified up to three parameters in both simulated and actual test data. Importantly, their implementation on a (new for the time) microcomputer was at the forefront of the coming revolution in computers.

In the 1980's researchers applied Kalman filter techniques on a wide variety of problem domains. These ranged from heave compensation [14], [15], and [16] to increasing the accuracy of ship navigation [17], to bearing-only position tracking [18]. With the advent of faster computers, Kalman filters were increasingly used to fuse data from multiple sensor systems/types and were combined with other techniques to increase prediction accuracy, efficiency, and utility. Raghunath and Carton [19] extended Kalman techniques to model and predict ocean dynamics and current circulation using multiple sensor data sources including bathymessage reports combined with GEOSAT data. Riedel and Healey [20] presented a sliding-mode controller (SMC) design that fused inputs from multiple sensors for wave prediction and estimation. Their methodology used an acoustic Doppler velocimeter and motion package instruments to provide estimates of wave-induced disturbances to a controller, thereby allowing an autonomous undersea vehicle (AUV) to maintain both position and heading with great accuracy.

Huster et al [21] presented innovative work fusing vision-based bearing together with inertial rate sensor data using a Kalman filter for estimating the relative position of AUVs. Results, based on tests using a laboratory testbed with a robotic manipulator demonstrated the ability to accurately estimate relative positions between a free-floating vehicle and a stationary object. Their results proved their estimator was capable of performing object localization and pick-up tasks in a non-stationary environment. This presented a major advance for autonomous operational control and deployment of AUVs. In a paper presented in 2003, Pace

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et al [22] improved data association and filtering by employing passive narrow-band spectral features in conjunction with Kalman filters in a multiple-hypothesis tracker (MHT). Kinematic states are estimated using an iterated extended Kalman filter (IEKF). Using Bayesian MHTs together with passive narrow-band processing to generate features, their architecture combines kinematic and frequency attribute features to generate an association likelihood score. The application of Kalman filters combined with Bayesian theory has also been applied to passive tracking of surface and subsurface targets [23] and acoustic communications channel estimation [24] with impressive results.

III. ARTIFICIAL INTELLIGENCE

The concept of creating intelligent systems that mimic human cognitive capabilities has been a dream for over a century. Turing [25] is credited as the originator of the concept of machine learning as well as the modern computer. However, it wasn't until the advent of the personal computer that artificial intelligence (AI) could be realized as a viable technique to solve problems outside laboratory environments. Artificial intelligence can be defined as the science of programming computers to perform tasks that (typically) require human intelligence. The main areas of research focus on machine learning, reasoning, problem-solving, perception, and language-understanding.

Expert systems, one of the AI branches, have been used in oceans engineering systems since the 1980s. Williams [26] was perhaps the first to introduce this new technology to OCEANS in 1983. That same year several other OCEANS researchers presented work on expert systems, applying these AI techniques to the control of underwater robotic manipulator tasks [27] and AUV guidance [28]. Chappeli demonstrated the application of a knowledge-based system to monitor sensor performance for collision detection and avoidance. The researchers noted the challenges involved with defining the actual rules to use based on inputs from subject-matter experts, and the effect on the system efficiency as the number of rules increased.

A generalized methodology for introducing a knowledge-based system in ocean engineering applications was presented by Nayak [30] in 1988. This work presented a design framework for incorporating expert systems to minimize overall complexity, therein increasing their utility and efficiency. Lewis and Gwin [31] proposed an AI system for autonomous AUV command and control using a set of distributed, interlinked set of isomorphic AI systems. This paper was perhaps the first in oceans technologies to present an agent-based approach with multiple agents performing high and low-level tasks, working together in a time-ordered hierarchy. In the next few years AI systems were designed to classify objects from sonar returns [32] and to reduce the operational downtime of drilling platforms due to drifting icebergs [33].

Merrill et al [34] researched the challenges of designing languages that facilitate communication between multi-agent AI systems controlling AUVs. Their analysis of natural languages allowed them to formulate communicative 'act types', and formalize a set of minimally required functional components to perform robust, adaptive communication in uncertain environments. This important work defined mechanisms to resolve the challenges of integrating multiple control systems for all ocean-based autonomous systems.

IV. COMPUTATIONAL INTELLIGENCE

Computational intelligence (CI), often known as 'soft computing', is a rubric encompassing artificial neural networks (ANNs), fuzzy computing, and evolutionary algorithms. While some CI techniques are often counted as artificial intelligence techniques (e.g. evolutionary algorithms and neural networks) there is a definite difference between these techniques and traditional, logic-based artificial intelligence techniques. Current consensus holds artificial intelligence techniques as top-down approaches to solving problems (i.e., the model structures, solutions, etc. are imposed from above). Computational intelligence techniques are generally bottom-up, with order and structure emerging from an unstructured (e.g., random) beginning.

Artificial Neural Networks

Artificial neural networks (ANNs) have received considerable attention in recent years. ANNs have the advantage of being very flexible models. They accept input and generate outputs, and when parameterized appropriately, they can be shown to be able to compute any measurable function [35]. Such a function can represent a transformation from data collected from a sensing device to a classification of whether or not a specific type of signal is present. The flexibility of ANNs has been a leading motivation for their use in pattern classification/recognition problems.

Artificial neural networks (or simply *neural networks*) are computer algorithms loosely based on modeling the neuronal structure of natural organisms. Neural networks are modeled as parallel-processing structures consisting of nonlinear processing elements interconnected by fixed or variable weights. They are typically used to learn an input-output mapping over a set of examples (e.g.,

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spectral feature inputs from seismic sensors mapped to outputs consisting of decision types of stimuli passing the sensors). ANNs are quite versatile, for they can be constructed to generate arbitrarily complex decision regions for stimulus-response pairs. That is, in general, if given sufficient complexity, there exists a neural network that will map every input pattern to its appropriate output pattern, so long as the input-output mapping is not one-to-many (i.e., the same input having varying output). An example of a feed-forward ANN is shown in Fig 2.

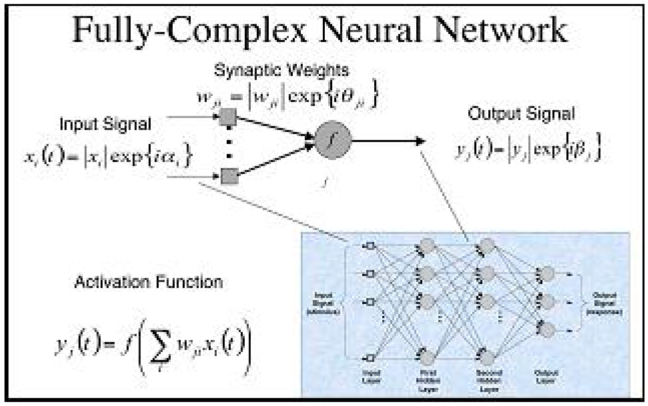

Figure 2. Feed-forward ANN topology with fully complex inputs and outputs.

Neural networks are therefore well suited for use as detectors and classifiers. Classical pattern recognition algorithms require assumptions concerning the underlying statistics of the environment. Neural networks, in contrast, are nonparametric and can effectively address a broader class of problems.

Researchers solved many of the previous problems relating to training ANN architectures in the 1980s, resulting in their application in many scientific disciplines including oceans technologies. One of the largest and most successful application areas is the use of ANNs for pattern recognition, classification and detection. The first application of ANNs presented in an OCEANS' conference proceedings was in 1989, where Maccato, A. and de Figueiredo [36] described a neural network framework for detecting and classifying transient acoustic signals in the presence of noise. Scale-space contour features mapped onto a hierarchical tree structure were input to a feed-forward neural network architecture that generated classification outputs. ANNs have been used to interpolate seafloor sediments where only sparse measurements are available. Caiti and Parisini [37] designed a radial-basis neural network that was able to generate a continuous mapping of various sediment properties as a function of the three-dimensional position of the sediment measurements. Other related classification/detection problems tackled with ANNs include automatic object recognition systems using synthetic pattern imagery [38], pollutant induced tissue changes in fish livers [39], plankton recognition [39], seafloor imagery [40], [41], and mine detection [42].

ANNs are particularly well-suited to controlling systems in dynamic non-linear environments. Neural networks also offer the ability to design nonlinear controllers without requiring complex system models. In one of these systems, a neural-controller environment (SIGNAL) has been created to specifically assist in development of a variety of marine vessel control loops [43]. Other control applications include depth controllers for UUVs [44], current prediction in shallow water environments [45], and adaptive heave compensation [46]. An ANN has also been used to synthesize a robust velocity control system for a Remotely Operated Vehicle (ROV). Researchers Pollini and Nasuti [47] incorporated a feedback linearization controller (FBLC) in conjunction with a neural network with successful results.

Chaotic modeling of radar backscattering from an ocean surface has been performed via the use of neural networks. In a study by Haykin and Leung [48], radar backscatter (sea clutter) was modeled using radial basis function networks. This research used radar data to demonstrate the applicability of chaos theory for modeling sea clutter. ANNs have been combined with Kalman filters for motion model tracking and prediction. Owen and Stubberud [49] designed a neural extended Kalman filter (NEKF) that adapts online to unmodeled dynamics and/or nonlinearities for tracking air target trajectories. ANNs have also been recently been used for wave forecasting using buoy data [50].

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Fuzzy Logic

Lofti Zadah [51] enlightened the world to fuzzy logic in the early 1960s as alternative to the crisp logic of traditional mathematics. In classical logic an element belongs to a set as a binary function - it either does or it doesn't belong to the set. Fuzzy logic allows for degrees of inclusion in sets, and offers an alternative to randomness for describing uncertainty. Fuzziness describes the ambiguity of an event's occurrence, and like classical mathematical definitions of randomness, it also defines uncertainty numerically. Fuzziness is a measurement of the degree to which an event occurs, not whether or not the event actually occurs.

Fuzzy sets provide a natural way for handling problems without sharply defined criteria for class membership. The technique is particularly suited to handle continuous variables and noisy data, such as those typically found in ocean science problem domains. As opposed to crisp sets that only admit binary (0 or 1) outputs, fuzzy membership functions transform a numerical value into a graded state between 0 and 1 as shown in Fig. 3. Fuzzy logic is computationally fast since it uses relatively simple operators (e.g., min/max). This new logic system provides powerful opportunities to solve problems where previous strategies using classical logic proved ineffective, at best.

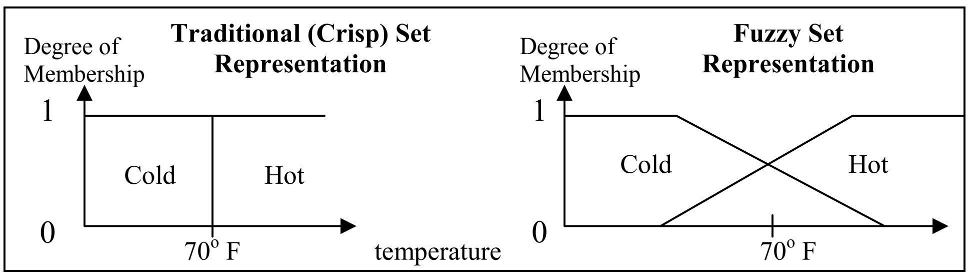

Figure 3. Traditional (crisp) set and fuzzy set membership functions.

The mathematics of fuzzy logic (and fuzzy sets) obey many of the same laws as traditional mathematical logic. Both systems combine sets (and propositions) and obey laws of association, commutativity, and distribution. A principle distinction between classical logic and fuzzy logic occurs in how each system jointly treats the set $\boldsymbol{A}$ and its opposite (complement) $\boldsymbol{A}^c$. In classical set theory, $\boldsymbol{A} \cap \boldsymbol{A}^c = \mathbf{P}(\emptyset) = 0$, and this intersection representing a probabilistically infeasible event. Fuzzy set theory admits degrees of inclusion (membership) within sets. Therefore, in fuzzy logic $\boldsymbol{A} \cap \boldsymbol{A}^c \neq 0$.

Li, et al [52] implemented a combination Fuzzy-Expert system to identify noise radiated from underwater targets (i.e., submarines, UUVs). In this study, fuzzy classifiers were incorporated to cluster frequency spectra features that were then passed through the expert system. A few years later fuzzy logic was implemented within a heuristic position estimator (HPE) navigation system by An et al [53]. Their heuristic estimator performed asynchronous data fusion of all sensor measurements based on confidence levels. These estimates were then combined with inertial navigation system (INS) inputs via a fuzzy filter. Results of this approach compared favorably with respect to traditional EKF-based implementations [54].

Fuzzy systems have also been implemented in a variety of other application areas to solve outstanding problems inherent in traditional approaches to their solution. Song and Smith [55] presented research on a fuzzy system that optimized both pitch and heading using a 6-degree of freedom model. Their design used a globally directed random search optimization technique to optimize the parameters of the fuzzy controllers operating in a quantized search space. The continuous state space was divided into a finite number of cells, with each cell providing direct information about the system's global dynamics (e.g., fixed points, domains of attraction for limit cycles). In addition to being able to automatically create the fuzzy rule sets, their resulting system also outperformed fuzzy sliding-mode controllers previously designed by experts with respect to cell state space constraints.

Multiple fuzzy controllers were used to control a rudder roll damping system. In this system, Nejim [56] proposed an architecture that combined two separate fuzzy controllers (one each for yaw and roll control) together with a fuzzy gain scheduling algorithm. There are many benefits to this approach over traditional linear control mechanisms. In test simulations the magnitude of the roll motion was lower with the fuzzy yaw and roll controllers when compared to the standard proportional-derivative (PD) methods, and the fuzzy gain scheduler was shown to reduce the effects of the limited actuator rate. Ghommam et al [57] developed a fuzzy-logic system to coordinate the paths of multiple underactuated vehicles. Two proportional integral derivative (PID) controllers were used in this study - a standard PI for controlling thruster speed and a second fuzzy controller for controlling rudder angle.

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The guided formation control approach used path following. Since the decentralized solution does not rely on a leader, it has wide applicability across a very general variety of paths.

Control of robotic manipulators is another area in which fuzzy systems have proven quite fruitful. Xu et al [58] designed and demonstrated a PD-fuzzy logic controller for a 5-degree of freedom underwater robotic arm manipulator system. Fuzzy logic was used to adaptively control the system gains. Their results showed that the system was both more robust and energy efficient (with respect to tracking in the presence of modeled hydrodynamic forces) when compared to a conventional PD-controller. Soylu et al [59] proposed a fault-tolerant fuzzy logic-based unmanned robotic vehicle manipulator (URVM) mechanism that addresses the challenges of multiple redundancy resolution. Instead of the previous task-priority approaches, they combined a gradient projection method (GPM) with fuzzy logic controllers. The fuzzy system automatically compensates for robotic arm breakdowns (e.g., joint failure, lost driving capacity, excursions outside joint velocity limits).

Evolutionary Algorithms

Evolutionary algorithms (EA) are paradigms based on the concept of Darwinian evolution to iteratively generate increasingly appropriate solutions (the behavior of organisms) in light of a static or dynamically changing environment. This differs from other artificial intelligence research that largely centers on the search for simple heuristics (generally useful rules) derived from subject matter experts (SMEs). Instead, evolutionary algorithms evolve a set of solutions solve problems with regard to the operational environment and specified payoff function. Evolutionary algorithms may be considered an optimization technique wherein the algorithm iteratively optimizes behaviors, parameters, and/or other constructs.

All evolutionary computation algorithms (e.g., evolutionary programming, genetic algorithms, genetic programming) have four major components: initialization, variation, evaluation (scoring), and selection. The basic evolutionary algorithm starts with a population of trial solutions (i.e., parents) initialized by random, heuristic, or other appropriate means. Each of the parent members is then altered through application of a variation process. Each 'parent' member *i* generates $\square_i$ progeny which are replicated with a stochastic error mechanism (e.g., mutation). These solutions are then all evaluated over the existing environment in the same manner. A selection process is then performed to cull the least-fit solutions from the population. The process iterates until the termination criteria is achieved. Fig. 4 diagrams this process pictorially.

t:=0;
initialize $P(0) := \{a'_1(0), a'_2(0), \ldots, a'_\mu(0)\}$
evaluate $P(0) : \{\Phi(a'_1(0)), \Phi(a'_2(0)), \ldots, \Phi(a'_\mu(0))\}$
iterate
{
variation: $P'(t) := m_{\Theta_m}(P(t))$
evaluation: $P'(t) : \{\Phi(a'_1(t)), \Phi(a'_2(t)), \ldots, \Phi(a'_\lambda(t))\}$
selection: $P(t+1) := s_{\Theta_s}(P'(t) \cup Q)$
t := t + 1;
}

where

a' is an individual member in the population
$\mu \geq 1$ is the size of the parent population
$\lambda \geq 1$ is the size of the offspring population
$P(t) := \{a'_1(t), a'_2(t), \ldots, a'_\mu(t)\}$ is the population at time t
$\Phi : \mathrm{I} \rightarrow \Re$ is the fitness mapping
m_{Θ_m} is the variation operator with controlling parameters Θ_m
s_{Θ_s} is the selection operator $\ni s_{\Theta_s}\ \mathrm{I}^\lambda \cup \mathrm{I}^{\mu+\lambda} \rightarrow \mathrm{I}^\mu$
$\mathrm{Q} \in \{\varnothing, \mathrm{P(t)}\}$ is a set of individuals additionally accounted for in the selection step, i.e. parent solutions.

Figure 4. A generalized evolutionary algorithm paradigm

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The first application of evolutionary algorithms within the perspective of OCEANS can be found in Fogel [60]. In this pioneering research, an evolutionary program was created to optimize autoregressive moving average (ARMA) models of transient acoustic data (e.g., ice cracking). The evolved ARMA models demonstrated the efficacy of the technique as a general-purpose model optimization tool. Porto [61] showed how evolutionary algorithms were also used to localize non-acoustic (magnetometer) arrays. A far-field dipole model was assumed with the parameters optimized to minimize error residuals over the sampled data time series. The evolutionary methods significantly outperformed traditional (i.e., variable-metric) least squares optimization techniques in this study.

McGookin et al [62] applied a genetic algorithm (GA) to optimize a course changing control system for tankers. The genetic algorithm optimized a sliding mode controller with quite impressive performance over a range of operational environments. Their research demonstrated the optimized controller tracked the desired response with minimal error and, importantly, that the rudder motion was well within the limit range of the control actuator.

In Seong and Park [63] acoustic data inversion was optimized using a genetic algorithm. A genetic algorithm optimized shallow water speed of sound and boundary layer thickness models. Whereas traditional inversion via *a priori* estimation of the sound speed and layer thickness is achieved entirely through the arrival time of the waves, the GA optimized models used all of the information in the signals, thus are expected to provide more robust results in a variety of noisy environments.

A combination of traditional and evolutionary techniques was used to address the problem of mine detection and classification [64]. The common two stage approach uses image segmentation preprocessing to extract features that are subsequently classified. Any feature extraction errors (e.g., outliers) can propagate through the process chain resulting in suboptimal classification performance. Quidu et al used a genetic algorithm that evolved flexible models derived from 2-D Fourier transform coefficients of the shallow water image contours, with classification performed directly from this data.

Other interesting applications of evolutionary algorithms include both optimizing communication system designs and path/route planning. Dhanoa et al [65] used an EA to obtain accurate estimates of the Doppler spread for a high data rate underwater digital acoustic communication system. Their approach was based on suppressing multipath interference instead of by equalization, which can be problematic since the channel is doubly spread (time delay and Doppler). The EA optimized the estimated Doppler spread, and their results demonstrated the system outperformed more traditional Fourier-based methods in both dynamic range and frequency resolution. A GA has also been used to plan optimal paths for AUVs. Wang et al [66] researched the ability of GAs to optimize AUV paths in an obstacle-rich environment. This novel approach used a 3-D discrete spatial model with multiple distance scales encoded into the GA chromosome. The resulting plans demonstrated the capability to plan and dynamically navigate through multiple obstacles in real or near-real time.

V. THE PERSONAL COMPUTER, WORLD WIDE WEB, AND THE INTERNET

The reduction in both the size and cost of computers has perhaps had the largest impact on oceans science. Prior to the advent of the personal computer (PC), computational tasks were largely carried out on large, land-based computers that often required days, if not month of time to perform what are now considered relatively minor computational tasks. Before the PC became widely available, however, ocean scientists were using both shore-based and ship-based computers to process data. Prada et al [67] was one of the first papers to detail the state of sea-based computer systems. They described the then state-of-the-art digital computer systems for data acquisition and processing data for various studies including navigation, magnetic, gravity, bottom profiling, and seismic studies. Multiple minicomputers (predecessors of the modern PC) were employed on the research vessel ATLANTIS II. Incredibly, real-time processing and display of seismic signals was demonstrated, although more complex processing tasks were performed ofline after storing data to tape. They noted achieving this state of computation at sea (something we take for granted today) was the culmination of several years of effort. Perhaps presaging a coming trend, they also noted that the ship-based minicomputer data processing costs were "substantially lower than could be expected by shore-based computer systems."

Computer technology was sufficiently advanced in 1975 to simulate underwater missions used in the parametric design undersea vehicles. The simulations used by Cantwell and Cap [68] incorporated vehicle dynamics (e.g., launch, dive, rendezvous, replenishment) over a defined mission space to evaluate different candidate propulsion systems. They speculated that their computerized approach could be applied to the design of support ship, support facilities costs, and, someday, potentially vehicle control and sonar and optical sensor performance equations. Two years later Dekja [69] presented an updated survey of the minicomputers. Dekja predicted that, because of the newly defined IEEE 488B standard bus interface, microcomputers would be employed as 'rack and stack' components in both multipurpose roles as well as for application specific (e.g., FFT) processing tasks. By 1982 another survey by Rosenblum and Clamons [70] described the tradeoffs between processor size, speed, input/output (I/O) capabilities, and general-purpose versus specific large scale integrated (LSI) and very large scale integrated

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(VSLI) processor capabilities. Intriguingly, they describe the need for better systems for interconnecting multiple computers to handle the rapidly increasing need for sharing data between them in an efficient, standardized, and convenient manner. By 1986 the concept of a 'multicomputer' that could accommodate multiple users and share files with other computers appeared in an OCEANS conference [71]. This paper also described how parallel processing would soon become a reality, realized by a network of linked computers, each performing one or more subtasks in an organized process.

The PC was used on ocean vessels as early as 1987. Branton and Clay [72] presented results of a study that compared and contrasted four different PC configurations for use in oceanography applications. They showed how PCs could be interconnected to collect, process and analyze data with standardized input and output formats that allowed file sharing between multiple applications (e.g., spreadsheets and graphics packages). They noted that the familiarity with land-based PCs would soon lead to their widespread application in ocean vehicles. Interestingly, signal processing using spreadsheet applications was a presentation topic the following year [73].

It would be remiss to neglect the impact that the internet and the world wide web have had on ocean science. Twenty years ago data transmission was a common problem, with relatively little data sharing across the field due to the cumbersome nature of the data storage and transmission mechanisms. The internet and web have opened the door to rapid and easy access to a wealth of data, with real-time access to data streams, computational capabilities, and peer review. The satellite-based global positioning system (GPS) has also contributed greatly to information processing technology in the ocean sciences, as it provides position localization with previously unimaginable accuracy.

VI. A PEEK INTO THE FUTURE

The aforementioned advances in information processing technologies only hints at the potential for these techniques to solve ocean science problems. It is reasonable to expect further breakthrough technologies in the future, especially with respect to real-time systems. Online *in-situ* learning will become ubiquitous through a combined use of ANNs, evolutionary algorithms, fuzzy sets, and yet-to-be discovered technologies. This will realize a long-standing objective of creating truly autonomous vehicles to perform cooperative and coordinated tasks. Intelligent sensor systems will be integrated for onboard fault diagnosis and prediction. Imagine an online intelligent system that can predict incipient failure of a hydraulic pump or propeller driveshaft with sufficient time to make necessary repairs.

It is important to note that Kalman filters, Expert Systems, ANNs, evolutionary, etc. algorithms are only tools in a multifaceted toolbox. We have already seen ANNs, fuzzy logic, and evolutionary algorithms successfully integrated into hybrid systems. By combining the useful properties of these information processing tools together with new visualization tools, ocean scientists will be able to solve many previously intractable problems. Future IP systems will depend on the integration of several of these advanced tools to better solve problems. The inherent and unique capabilities of each tool will be exploited instead of relying on a singular technology to solve the entire problem.

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