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Navigation Technologies for Autonomous Underwater Vehicles

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***Abstract*—With recent advances in battery capacity and the development of hydrogen fuel cells, autonomous underwater vehicles (AUVs) are being used to undertake longer missions that were previously performed by manned or tethered vehicles. As a result, more advanced navigation systems are needed to maintain an accurate position over a larger operational area. The accuracy of the navigation system is critical to the quality of the data collected during survey missions and the recovery of the AUV. Many different methods for navigation in different underwater environments have been proposed in the literature. In this correspondence paper, the state of the art in navigation technologies for AUVs is investigated for theoretical and operational systems. Their suitability for use in different environments is compared and current limitations of these methods are identified. In addition, new approaches to address these current problems and areas for future research are suggested. Finally, it is concluded that only geophysically referenced methods will enable AUVs to navigate accurately over large areas and that advances in underwater feature recognition are required before these methods can be implemented in operational AUVs.**

***Index Terms*—Computational intelliqence, navigation, underwater vehicles.**

I. Introduction

Autonomous underwater vehicles (AUVs) were initially developed to perform missions that were impossible for tethered, remotely operated vehicles (ROVs) and are replacing ROVs and towed arrays for many missions [1]. Unlike unmanned underwater vehicles (UUVs) that are usually operated remotely by an acoustic modem link, AUVs present a uniquely challenging navigational problem because they operate autonomously in a highly unstructured environment where satellite-based navigation is not directly available. Unlike autonomous aerial vehicles, AUVs must navigate using other methods when submerged.

Their autonomy allows AUVs to be used for missions where a surface vehicle or manned submersible would be at risk, such as mine countermeasure (MCM) or under-ice operations [2]. When performing detailed surveys, AUVs can offer a more stable platform for precision sensors than towed arrays because they are not subject to physical disturbances transmitted along the cable to the surface vessel. This lack of physical attachment also allows AUVs to measure ocean characteristics at specific depths and perform bottom-following missions.

For an AUV to successfully complete a typical survey mission, it must follow a path specified by the operator as closely as possible and arrive at a precise location for collection by a surface vessel. If the final position of the AUV is not accurate, the AUV may be unrecoverable. If the AUV does not follow the path accurately during the mission, critical features may not be recorded and the position of any features recorded during the mission will be uncertain. The precision of the navigation system can directly affect the quality of the recorded data if image processing techniques are used to enhance areas that were observed multiple times during the mission and these areas are misaligned because of navigational errors.

While established techniques provide AUVs with reasonable navigation for most scientific missions, the operation of AUVs in restrictive environments that require more accurate navigation is more challenging. If an AUV is undertaking a covert mission or operating where the surface is inaccessible, methods that are practical for scientific missions become impossible to use. In these situations, the AUV cannot resurface to receive a GPS signal or make use of existing sonar beacons, so new methods that do not rely on the availability of such signals are needed.

The primary challenge in AUV navigation is maintaining the accuracy of an AUV's position over the course of a long mission. An initially accurate position can quickly become uncertain through variations in the AUV's motion. This effect can be reduced by using accurate acceleration, heading, and velocity sensors but these sensors cannot be made arbitrarily accurate. During long missions, these inaccuracies become significant. Strong currents and other underwater phenomena that affect the motion of the AUV but cannot be precisely modeled lead to greater inaccuracies.

If the position of the AUV is not externally referenced, the accuracy of position will inevitably degrade over the course of the mission. The lack of an easily observable, external reference makes AUV navigation very difficult. Any AUV navigation system that provides accurate navigation over long missions must use an external reference. Different methods of providing such a reference are surveyed in this correspondence paper. In restrictive environments, some of these methods may not be usable. By considering the problem of providing accurate navigation in these more restrictive environments, techniques may be developed that lead to more effective navigation for all AUV missions.

II. Navigational Methods

The different methods that are currently used for the AUV navigation can be grouped into three categories [3].

1) *Inertial navigation*: Inertial navigation uses gyroscopic sensors to detect the acceleration of the AUV. This is a significant improvement over dead reckoning and is often combined with a Doppler velocity log (DVL) that can measure the vehicle's relative velocity.
2) *Acoustic navigation*: Acoustic navigation uses acoustic transponder beacons to allow the AUV to determine its position. The most common methods for AUV navigation are long baseline (LBL) that uses at least two, widely separated transponders and ultrashort baseline (USBL) that generally uses GPS-calibrated transponders on a single surface vessel.
3) *Geophysical navigation*: Geophysical navigation uses physical features of the AUV's environment to produce an estimate of the location of the AUV. These can be preexisting or purposefully deployed features.

The current generation of AUVs are equipped with sensors that can make use of a combination of these methods during a single mission. The different sensor data obtained from each method need to be processed together throughout a mission to obtain an optimal estimate

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of the vehicle position. The techniques currently used for deriving an estimate of the AUV's position from this data are:

1) Kalman filters (KFs);
2) particle filters;
3) simultaneous localization and mapping (SLAM) and concurrent mapping and localization (CML) algorithms.

Both SLAM and CML algorithms will be referred to as SLAM algorithms.

Particular AUV navigation systems can combine these techniques to take advantage of their different characteristics. At time intervals during the mission, current navigation systems produce an estimate of the AUV's location and a description of the uncertainty of the AUV's position, often in the form of a 2-D Gaussian distribution. This is used by the AUV control system to determine the completion of mission objectives such as waypoints.

AUVs are deployed in a wide range of shallow and deep water environments that pose different challenges. Combinations of sensors used vary from mission to mission but a typical range of sensors will be available in a given environment.

1) *Shallow water surveys*: AUVs are currently used for bathymetric surveys and MCM in coastal waters and are being considered for port defence. Most surveys use side-scan sonars that have a broad swath in shallow water and can cover an area with a shorter mission path. Littoral waters often contain obstacles and local constraints such as shallows, harbor walls, and nearby vessels.
2) *Deep water surveys*: Long, deep water surveys are mainly undertaken by the oil industry and the geophysical sciences. Side-scan and multibeam sonars are often used along with a range of chemical sensors. It is usually impractical for an AUV to resurface during such a mission and acoustic beacons on surface vessels are often at the limit of their range. The underwater environment is usually sparse but fishing nets can easily disable an AUV and the large mission area can make retrieval difficult.
3) *Sea floor feature tracking*: Maintenance missions such as pipeline or cable surveys are done in both deep and shallow water in conjunction with an ROV and usually require a combination of visual sensors, subbottom profilers, and extensive on-board processing. The range of tracking missions is often limited by AUV endurance because of the higher power requirements of the sensors and the need to provide illumination for optical sensors.

A. Inertial Navigation

While inertial navigation systems (INS) can be fitted to inexpensive AUVs, high performance INS are limited to more expensive AUVs due to the difficult production of fiber-optic gyroscopes. Since the accelerometers of an INS are subject to drift, especially if the AUV follows a linear course, navigation systems that only use INS experience a gradual degradation of position over time. In order to improve performance for longer missions, a DVL sonar can be used to measure the speed of the sea floor relative to the AUV. Similarly, an acoustic Doppler current profiler (ADCP) sonar can measure the relative speed of the local current. DVL sonars have a limited range and can only be used when the AUV is near to the sea floor. However, when using both INS and DVL, the estimate of position is still subject to drift over time. If such a system is used to perform long missions, it must reset this navigational drift by determining its position relative to an external reference point. This can be done directly by resurfacing and using a GPS receiver but this is undesirable during deep water surveys and impossible if the surface is inaccessible due to ice.

Monterey Bay Aquarium Research Institute recorded the performance of an integrated INS and DVL unit with an AUV in preparation for the Atlantic Layer Tracking Experiment (ALTEX) [4]. The DVL was used to track the relative movement of the ice above the AUV instead of the sea floor. While calibration difficulties were experienced with the INS, DVL, and gyro-compass sensors, the feasibility of the navigation system for the planned survey was confirmed. The Autosub team have also done extensive research into the operation of an AUV under ice using INS, DVL, and ADCP sensors [5]. They achieved a postprocessed accuracy of around 0.2% of the mission distance but performance was limited by the accuracy and consistency of the ADCP.

When an INS, DVL, and GPS are combined, the AUV must derive an estimate of its position from sensors that have very different characteristics. A popular way of deriving an estimate of position from the sensors is to use a KF [6]. This allows the growing uncertainty of the position estimate from the INS to be reduced using GPS fixes by assigning a time-dependent variance to the INS signal and a constant variance to the GPS signal.

The KF estimates the state of a system from a sequence of uncertain observations using a predict–update cycle. First, a predictive estimate of the next state and its uncertainty is made using an existing physical model and a statistical model that describes any uncertain factors such as process noise. This prediction is then updated using an observation of the process depending on the difference between the prediction and the observation and their uncertainties. Once this updated estimate has been calculated, a new predictive estimate can be made.

The KF is the optimal Bayesian estimator of the state if the system is Markovian, linear and any uncertainties are Gaussian [7]. For such a system described by the state vector $\mathbf{x}_{k-1}$ and covariance vector $\mathbf{P}_{k-1}$ at time $k-1$, the next state of the system is defined as $\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{v}_{k-1}$ where $\mathbf{F}_{k-1}$ describes the physical model and $\mathbf{v}_{k-1}$ describes the Gaussian uncertainty. Similarly, the observation vector is defined as $\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{w}_k$ where $\mathbf{H}_k$ describes the physical model of the observation process and $\mathbf{w}_k$ describes the uncertainty. Both vectors $\mathbf{v}_{k-1}$ and $\mathbf{w}_k$ are defined as being generated by zero-mean Gaussian distributions with covariances $\mathbf{Q}_{k-1}$ and $\mathbf{R}_k$, respectively.

The predictive and updated estimates of the state vector are computed by the equations

$$\begin{aligned}
\hat{\mathbf{x}}_{k|k-1} &= \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1}\\
\mathbf{P}_{k|k-1} &= \mathbf{Q}_{k-1} + \mathbf{F}_{k-1}\mathbf{P}_{k-1}\mathbf{F}_{k-1}^T\\
\hat{\mathbf{x}}_k &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\left(\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1}\right)\\
\mathbf{P}_k &= \mathbf{P}_{k|k-1} - \mathbf{K}_k\mathbf{S}_k\mathbf{K}_k^T
\end{aligned}$$

where $\hat{\mathbf{x}}_{k|k-1}$ and $\mathbf{P}_{k|k-1}$ are the predictive estimates of the state and covariance vectors, $\hat{\mathbf{x}}_k$ and $\mathbf{P}_k$ are the updated estimates, and

$$\begin{aligned}
\mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{H}_k^T\mathbf{S}_k^{-1}\\
\mathbf{S}_k &= \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k
\end{aligned}$$

where $\mathbf{K}_k$ is the Kalman gain and $\mathbf{S}_k$ is the covariance of the $\left(\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1}\right)$ term. It can be seen that the updated estimate $\hat{\mathbf{x}}_k$ differs from the predictive estimate $\hat{\mathbf{x}}_{k|k-1}$ depending on the difference between the observation $\mathbf{z}_k$ and the predicted observation $\mathbf{H}_k\hat{\mathbf{x}}_{k|k-1}$. The effect of this difference is dependent on the Kalman gain that is large when the variance of the prediction $P_{k|k-1}$ is larger than the variance of the observation $\mathbf{R}_k$. In this way, predictive estimates are updated by the KF by a larger amount when the observations are more certain. A complete description of a KF suitable for use in an AUV navigation system can be found in [8].

If the physical system describes the motion of an AUV, the physical model can be highly nonlinear. In this case, the assumptions of the KF break down and the optimal Bayesian estimate of the process cannot be easily found. An extended Kalman filter (EKF) can be used to extend the KF to nonlinear models by using a first-order Taylor series to approximate the nonlinear processes. The partial derivatives of the physical models are taken using a Jacobian matrix and added to the linear estimates while the predict-update cycle remains identical to the KF. The derivation of the Jacobian matrices needed is often nontrivial and adds to the complexity of implementation. Also, in highly nonlinear problems, the EKF tends to underestimate the variance of the state that can lead to large inaccuracies.

The EKF has been shown to perform well for navigation with an INS and DVL provided it is updated regularly with GPS or other reference signal. However, its performance will inevitably degrade rover time if GPS is not available [9]. This degradation will be faster when using low-cost sensors but high- performance INS/DVL sensors can be used to achieve 0.01% accuracy over short (2.5 km) missions that follow a circular path [10]. This represents an order of magnitude increase in accuracy over less expensive sensors.

The unscented Kalman filter (UKF) uses statistical linearization in place of the analytical linearization of the EKF. The statistical linearization uses the unscented transform [11] that approximates a nonlinear function using a set of points that are chosen systematically to ensure that higher order terms in the Taylor series of the nonlinear function are approximated. The predictive estimate is calculated by applying the physical process model to these points and taking the weighted mean of the points as the predicted observation. The UKF can accurately calculate the mean and variance of the state if the uncertainties are Gaussian. However, if the uncertainties are not Gaussian, the UKF's description of the uncertainties may be inadequate. In this situation, the number of points used can be increased to model the higher order moments of the underlying uncertainties [12].

While it is necessary to calculate the square root of the nonlinear distribution, this is a less computationally intensive operation than calculating a Jacobian matrix. However, the UKF has not yet been implemented as part of an operational AUV navigation system. Recent advances in mobile computing power suggest that the primary impetus for implementing a UKF would be its greater accuracy for nonlinear systems rather than its computational efficiency [13].

Particle filters can also be applied to the problem of inertial navigation [14]. A particle filter can be used to approximate the probability density function of the position vector x_t as a set of N different position vectors $\{x_t^{(i)}\}_{i=1}^{N}$, each with an associated, normalized weight $w_t^{(i)}$. Similarly to other Monte Carlo techniques, the parameters of the N position vectors are each chosen at random from suitable distributions. All of the particles are then used to generate individual predictions of the next observation vector z_1 according to the physical model. When the observation vector z_1 is available, the weights of each of the particles are updated to reflect their accuracy.

Particle filters are not subject to the restrictions of KFs and are capable of accurately modeling highly nonlinear functions when the underlying uncertainties are not Gaussian. However, they are far more computationally intensive than KFs because their accuracy depends on a large number of particles being modeled. This is a major disadvantage for AUVs that are navigating using only INS since they are often smaller vehicles that have limited power and processing and particle filters have not been used to combine INS/DVL/GPS signals for AUVs. However, new techniques developed for land vehicles that change the number of particles used based on the current uncertainty in position can reduce these computational requirements [15].

While the nonlinear problem of inertial navigation requires sophisticated techniques to obtain optimal estimates of position using all available sensors, current methods have been shown to produce satisfactory results in AUV missions. The restrictions on navigational accuracy do not arise from the statistical methods used but from the open-loop nature of the sensors themselves. The current generation of AUVs can achieve high navigational accuracy using the latest INS but their accurate range is limited if only inertial navigation is used.

B. Acoustic Navigation

Acoustic navigation is defined here as any method that uses acoustic beacons present in the AUV mission area, regardless of their operation. While many different systems have been deployed, the two main methods are LBL and USBL. LBL systems require the installation of at least two beacons, usually on the sea floor, which immediately return an acoustic signal sent to them by the AUV. Using knowledge of the beacon positions, the local sound speed, and the time of flight of the signal, the AUV can deduce its position from the intersection of the AUV's possible positions relative to each beacons. USBL systems use a single beacon, usually attached to a surface ship. The current generation of USBL systems equip the beacon with an INS/GPS system to reduce the calibration requirements of the surface vessel [16]. Both methods have a range limited by the extent of the transponder network that is around 10 km for individual LBL and 4 km for USBL networks in deep water. In shallow water, the range of a USBL system can drop to less than 500 m. There is no theoretical limit to the extent of a beacon network but the cost of installation and maintenance makes such an approach impractical for many missions. Both systems require calibrated and aligned beacons and corresponding calibration and programming of the AUV.

If the location of the beacons is not provided in advance, SLAM techniques can be used to generate a map of the beacon network and use it to aid navigation. Such a map needs to be a stochastic map that is able to express the uncertainties in position of the features recorded on the map that arise from inaccuracies in the vehicle's movement and sensors [17]. The process of generating a map and determining an autonomous vehicle's position on that map over the course of a mission is also referred to in the literature as CML. SLAM techniques can construct a map using only observations of beacons during the mission and do not require prior knowledge of the location of the beacons [18]. In order to use such a system, an AUV mission area could be prepared by deploying many inexpensive, disposable sonar beacons.

In theory, autonomous mapping techniques are not limited to the use of artificial beacons and have been demonstrated for robot navigation in structured indoor and outdoor environments without artificial landmarks [19], [20]. Research has been done using forward-looking, multibeam sonar where the state vector is augmented to include descriptors of individual landmarks [22]. The definition and extraction of these individual landmarks can be difficult and although a general Bayesian framework for identifying visual landmarks that are suitable for SLAM has been proposed [21], the performance of a similar framework in an unstructured, underwater environment has not been investigated.

While autonomous recognition of artificial features has been successfully used to enhance mosaics derived from side-scan sonar data, there are no details of the reliability of this method [23]. The absence of subsequent advances in this area may imply that underwater, sonar-based SLAM techniques are currently only suitable for use with networks of acoustic beacons because of the unstructured nature of the underwater environment, the corresponding lack of suitable features for recognition, and the inability of existing algorithms to reliably extract naturally occurring features from sonar data. While beacon-like features can be observed where there are man-made objects, such as inside harbors and shipping lanes, it is likely that acoustic navigation systems such as LBL will be economic to install in these environments, and therefore, more suitable for accurate navigation.

A SLAM algorithm uses an initial, uncertain position and subsequent observations of beacons to continually calculate the location of the vehicle and a corresponding map of its surroundings. The map augmented Kalman filter (MAK) filter in [18] gives a detailed description of the implementation of such a system. At time $t = k$, the position of the vehicle and the map can be described by the vehicle state vector $x_v(k)$, a sequence of observations $z(k)$, and a set of n beacons $\{x_b^i(k)\}_{i=1}^n$ where the vector $x_b^i(k)$ describes the location of beacon i at time k. To express covariances between the state vector and the beacon positions, it is necessary to combine the current state vector and the locations of the beacons as an augmented state vector

$$x_{\rm aug}(k) = \begin{bmatrix} x_v(k)^T & x_b^1(k) & \ldots & x_b^n(k)^T \end{bmatrix}.$$

This allows an EKF to be implemented that can track all the correlations between errors in the vehicle position and the position of the beacons in a single matrix

$$P_{\rm aug}(k) = \begin{bmatrix} P_{vv}(k) & P_{v1}(k) & \ldots & P_{vn}(k) \\ P_{1v}(k) & P_{11}(k) & \ldots & P_{1n}(k) \\ \vdots & \vdots & \ddots & \vdots \\ P_{nv} & P_{n1}(k) & \ldots & P_{nn}(k) \end{bmatrix}$$

where $P_{vv}(k)$ is the covariance of the vehicle state vector $x_v(k)$ when $t = k$, $P_{ii}(k)$ is the covariance of the beacon vector $x_b^i(k)$ and the off-diagonal vectors $P_{ij}(k)$, $P_{vi}(k)$, and $P_{iv}(k)$ are the vehicle-feature and feature-feature cross-correlations [24]. When a new observation z_{k+1} is made, the augmented matrices $x_{\rm aug}(k)$ and $P_{\rm aug}(k)$ are updated using the particular CML algorithm.

The accuracy and stability of such a SLAM algorithm depends critically on the statistical models used by the update filter. Depending on the implementation of the SLAM algorithm, it may be possible to destabilize the algorithm using badly formed initial conditions for the algorithm. This problem is avoided in [25] that presents a constant-time solution by using a system of submaps, each referenced from an individual, local beacon that has the most accurate, globally referenced position.

Conventional SLAM methods involve extensive calculation that increases exponentially with the number of beacons used. An alternative approach is to use the information form of the EKF to construct a sparse covariance matrix $P_{\rm aug}$ that reduces the computation complexity [26]. However, it is shown in [27] that enforcing sparsity can lead to an inconsistent global map. This results from the assumptions of conditional independence between the vehicle and the features that have been sparsified. The proposed solution to this inconsistency is to use an optical sensor to construct a delayed-state information that is exactly sparse but side-scan sonar.

As the vectors $x_{\rm aug}$ and $P_{\rm aug}$ are augmented with additional beacons, the computational requirements of a SLAM algorithm can increase as $O(n^2)$ where n is the number of landmarks used by the algorithm [28]. The FastSLAM algorithm reduces the computational complexity by using a particle filter and Rao–Blackwell techniques and achieves $O(m \log(n))$ where m is the number of particles used in the filter and n is the number of landmarks [29]. However, the number of particles needed to map larger areas is unknown. Techniques have been proposed that offer a constant time, $O(1)$ increase in complexity and are convergent if the vehicle repeatedly returns to each local area [25].

The Australian Centre for Field Robotics [30] has investigated SLAM in an underwater environment. A tethered submersible used SLAM to successfully follow a line of sonar beacons in [31] and accurately estimate its position. The current inability of the SLAM system to use natural landmarks in practice was demonstrated by a nearby large reef that provided a distinctive sonar return. Unfortunately, the position of the vehicle during the mission was not externally referenced so the navigational performance of the SLAM algorithm could not be analyzed.

A more recent experiment using data collected from the GOATS '02 experiment demonstrated that it was possible to achieve a navigation precision with a SLAM system that was comparable to the accuracy achieved when the locations of the beacons were precisely known [32]. This implementation used filtering and voting systems to remove inaccurate range estimates and a voting scheme to establish approximate positions for each beacon. Once this has been done, an EKF was used to recursively updated a state vector augmented with the positions of the beacons and the corresponding covariance matrix.

Detailed performance of the constant time SLAM (CTS) algorithm compared to an $O(n^2)$ algorithm that calculates all covariances in $P_{\rm aug}$ is given in [33]. This simulation, also using data from the GOATS experiments [34], showed that the CTS algorithm performed similarly to the conventional $O(n^2)$ algorithm. However, despite the use of artificial beacons, data association was done manually for the algorithm. While there is nothing intrinsic to the CTS algorithm that affects the difficulty of automatic recognition of beacons, any such algorithm will not be usable as a navigation system for an AUV until this problem is solved.

A more detailed analysis of SLAM in an underwater environment using can be found in [35]. This paper uses data collected by a Remus AUV [36] during a ladder search survey of an area of the sea floor using side-scan sonar. The resulting images of the sea floor are then compared to images of the sea floor when either a Kalman–Rauch–Tung–Striebel (RTS) smoothing system or the CML–RTS smoothing system is used on the data. The RTS filter is be used to smooth the output of the Kalman or CML filter so that there are no sudden jumps in the AUV's recalculated trajectory when the AUV crosses over a previously traversed area and corrects its position by loop closing.

The images obtained from the CML-RTS system are shown to be superior to those obtained from the Remus AUV's navigation system. The CML-RTS system is also capable of correctly positioning landmarks after their location has been smoothed by the filter whereas the Kalman–RTS system incorrectly positions landmarks in the corrected data. There are also improvements to the continuity of the images when the CML–RTS system is used. However, the CML–RTS system is not automatic and required a human operator to pick out landmarks manually. This makes the system only suitable for off-line processing. Automation of the landmark recognition is described as an ongoing problem.

Automatic landmark recognition is one of the biggest challenges when implementing all SLAM algorithms because they are dependent on reliable identification of suitable features from different vehicle positions. Since the nature of suitable landmarks varies depending on the sensors and operational environment of an autonomous vehicle, proposed methods are often only suitable for particular situations. Automatic recognition of naturally occurring underwater features is particularly difficult because they cannot be readily described by simple geometric shapes.

C. Geophysical Navigation

Geophysical navigation systems, or terrain navigation systems, use observable physical features to obtain an estimate of the AUV's position. This can be done either by supplying the AUV with an existing map of the area or by constructing such a map over the course of the AUV mission. While techniques that use local magnetic or gravitational variations have been proposed along with methods for their use [37]–[39], the performance of an operational system has not been published. While there is extensive evidence that similar systems are used by mammals [3], the unavailability of suitable commercial sensors has limited research in this area. Reliable recognition of geological features such as tidal inlets and hydrothermal vents has been achieved using fusion of multiple sensors and trained neural networks but these features are rarely observable during a typical AUV mission [40]. Current research concentrates on the use of physical features that can be observed by sensors already fitted to most AUVs: sonar sensors and optical sensors.

If the AUV is required to stay submerged throughout the mission, then externally referenced, global navigational aids such as GPS are unavailable due to the attenuation of high-frequency electromagnetic signals in water. Additionally, it is often tactically or economically desirable to operate an AUV without the installation of acoustic beacons or the presence of nearby surface vessels. This is necessary for some mine countermeasure (MCM) missions and survey missions in environments that are inaccessible to surface vehicles. The aim of geophysical methods is to provide navigational performance similar to that of a GPS system.

The success of any geophysical navigation method is dependent on the presence of suitable features and the ability of the system to extract useful features from the sensor data. Autonomous feature extraction from sonar data and the associated classification problem is difficult because of the typically low resolution of the sensors and amorphous shape of natural features. In Section II-B, it was noted that the lack of reliable methods for identifying distinctive sonar features such as beacons currently prevents the use of SLAM techniques for geophysical navigation.

Optical sensors have been investigated in conjunction with automatic image registration techniques and results given for their performance using data from an ROV mission [27]. Registration techniques are of particular interest in an underwater environment because they do not require explicit classification of individual features in the same way as SLAM techniques. While limited improvements in position can be achieved over linear mission paths, these methods are most suitable for missions where the AUV returns to a previously visited area where any error caused by sensor drift can be reset to its previous levels. Underwater cameras can be used as reliable, high-quality sensors within a restricted range and any AUV dependent on an optical sensor for navigation would need to operate close to the sea floor. This is not a problem for AUVs used for sea floor feature tracking. However, optical methods require careful illumination and it is difficult to modify many existing commercial AUVs to provide suitable light sources.

A different system for SLAM using a camera and automatic recognition of previously visited areas using an augmented state Kalman filter (ASKF) is presented in [41]. A mosaic of the camera data over the course of the mission is constructed that is used to identify when the AUV crosses over its mission path. When a crossover is identified, the ASKF is used as a smoothing filter on the previous position estimates. In this way, the ASKF can correct the entire estimated mission path of the AUV when it reaches a previously visited area. This can be used to check completion of mission objectives during an AUV mission. The performance of this system was tested using an AUV simulator developed for the GARBI AUV. However, the simulation did not test the ability of the mosaic system to recognize previously visited areas using real AUV mission data that may include significant biases.

While automatic identification of naturally occurring underwater features remains a problem, it will be impossible to implement a reliable, feature-based, autonomous mapping system. However, it is possible to use existing maps of an area to aid AUV navigation. When using an existing map, underwater feature recognition becomes less challenging because their description and position is already known. This method is of limited use to survey missions that are often undertaken in areas that have not been previously mapped. However, if an AUV needs to navigate precisely in a well-known environment such as the area surrounding a harbor, an existing map will often be available.

An advantage of using an on-board map is that the performance of the navigation system is not reliant on recognizing previously visited areas during the mission but instead depends on the variation of the local terrain. Critically, the method does not drift while the vehicle is operating in the area of the on-board map.

Extensive research has been undertaken into AUV navigation using high-detail terrain maps of selective areas that are generated from multibeam sonar surveys [42]. When an AUV is within one of these areas, it has been established that a multibeam sonar can be used together with a maximum-likelihood approach to estimate its position to within a few meters [43]. The computational demands of the method are high because the system performs calculations for over 80 individual sonar beams but these demands can be met by implementing the system as a field-programmable gate array (FPGA) [44]. However, the performance of the system is critically dependent on the availability of both a multibeam sonar and an accurate, high-detail map. If a lower detail map was to be used with this method, the system would offer poor performance due to the self-similarity of the terrain.

SLAM techniques can make use of an existing map to improve navigation performance by loading the augmented state vector with suitable feature locations and covariances. However, naturally occurring underwater features cannot be easily characterized by a single, identifiable point that is required by current SLAM algorithms. Unless a method can be found that can represent underwater features in this way, this suggests extensive modification of current SLAM methods is necessary to make optimal use of geophysical maps.

Particle filters have been investigated for navigation using existing maps [15]. Theoretically, a particle filter can provide estimates of the vehicle's position, heading, and velocity from geophysical sensors but the filter can be simplified if the AUV's existing sensors are used to provide the vehicle's heading and velocity.

A particle filter maintains an accurate estimate of the AUV's position by generating a large number N of state estimates $\{\mathbf{x}_k^i\}_{i=1}^N$ (which are called particles) and associated weights $\{w_k^i\}_{i=1}^N$ from an appropriate distribution at time k. When a observation $\mathbf{z}_k$ is made, the particles and their weights are updated using sequential importance sampling (SIS). If a particle filter starts with a wide distribution of particles, it takes time for the filter to stabilize [45]. However, since AUV missions launched from surface vehicles can be provided with an initial, GPS-referenced position, this is not a problem for AUV navigation.

All the particles and weights are used to calculate the current estimate of the AUV position. As more updates are made, the weights of many of the particles may approach zero while a small number of the particles will have large weights. This process is known as degeneracy and is particularly important when there is limited noise in the physical process. Degeneracy leads to a less accurate estimation of the state because the number of particles that are effectively used to estimate the state has been reduced. To counter this, the particles can be resampled when the measure of the number of effective particles $N_{\rm eff}$ falls below a threshold value $N_{\rm thr}$. The process of a general particle filter is given

Algorithm 1 A Re-sampling Particle Filter

1) Generate a large number of particles $\{\mathbf{x}_1^i\}_{i=1}^N$ and their associated weights $\{\mathbf{w}_1^i\}_{i=1}^N$ from an initial probability density function of the state vector $p(\mathbf{x}_1)$.
2) At time k, use the observation $\mathbf{z}_k$ to estimate the importance density $q(\mathbf{x}_k|\mathbf{x}_{k-1}^i, \mathbf{z}_k)$.
3) Generate N new particles $\{\mathbf{x}_k^i\}_{i=1}^N$ and their weights $\{\mathbf{w}_k^i\}_{i=1}^N$ from the importance density using SIS.
4) Estimate the effective sample size $N_{\text{eff}} = 1/\Sigma_{i=1}^N (w_k^i)^2$. If $N_{\text{eff}} < N_{\text{thr}}$ where N_{thr} is the threshold value, re-sample a new set of particles $\{x_{k'}^j\}_{j=1}^N$ with equal weights $\{w_{k'}^i\}_{j=1}^N$ from the existing weights using the statistic $P(x_{k'}^j = x_k^i) = w_k^i$.

in Algorithm 1. A more detailed discussion of specific particle filters can be found in [46].

For geophysical navigation, the calculation of the new particles must depend on the difference between an observed physical characteristic in the vector $\mathbf{z}_k$ and the value of that characteristic on the AUV's on-board map $h(\mathbf{z}_k)$. If an elevation map is used, this characteristic can be the depth of the sea floor directly below the AUV that can be accurately measured by a depth sensor and a bottom sounder. The distribution of the importance density in Algorithm 1 will be highly dependent on the local variance of $h(\mathbf{z}_k)$. In areas where there is little variance in $h(\mathbf{z}_k)$, the importance density will be uniform and the particles will become more dispersed.

Particle filters have been investigated for use with elevation maps for aiding underwater navigation and simulations suggest that such an approach is feasible [47], [48]. A significant advantage of this approach is that the filter does not rely on explicit classification of distinct underwater features. The particle filter is able to express the vehicle's location more accurately than a parametrized distribution because symmetries on the on-board map lead to estimates of the AUV's position that are often multimodal. However, the techniques used are highly dependent on the accuracy of the sensors and the map since the particle filter's performance is sensitive to the amount of noise present. Additionally, current AUV control systems that use waypoints require a unimodal estimate of position. For this purpose, a Gaussian distribution can be fitted to the particles and their weights but this introduces significant additional computation when large numbers of particles are used.

Using a particle filter effectively discretizes the estimate of the AUV's position. An earlier, alternative method that also discretizes the estimate is a point-mass filter [49]. However, the use of a particle filter makes it possible to use additional sensor information without significantly modifying the system and allows linear parts of the estimation process to be separated from the estimation problem using existing methods such as Rao–Blackwellization. The Rao-Blackwellization technique uses KFS to estimate the components of the state vector that can be described by linear, Gaussian processes. This approach requires significantly less computation because the integrations necessary to calculate the updated components can be performed analytically. A Rao–Blackwellized approach has been implemented and its performance tested on a simulation using an elevation map from survey data [48].

While the Monte Carlo methodology of the particle filter appears simpler to implement than the analytical requirements of the KF and SLAM algorithms when navigating from an existing map, the computational requirements of the method in its simplest form are very high. If techniques such as variable resolution particle filters or Rao–Blackwellization are used to reduce the computation, implementation becomes more difficult [48], [50]. For non-Gaussian signals, the choice of the importance density when updating the filter is also critical to performance and is not easy to decide [51].

III. Comparison

For short-range missions up to around 10 km, calibrated INS can provide sufficient accuracy for survey missions, regardless of the path taken by the AUV. This can be augmented with a DVL or acoustic navigation system if greater accuracy is required. For longer range missions up to 100 km, the path taken by the AUV has a large effect on the accuracy of the navigation system used. The discussed SLAM techniques correct incremental inaccuracies in the AUV's position when it returns to a previously visited area. This is necessarily true for any technique that uses a map generated over the course of a mission. If the AUV's path contains many crossover points, then these mapping techniques will perform well. Conversely, if the AUV follows a linear path or a single large loop, these techniques provide only a limited improvement from the resulting sequential registration of landmarks and will not significantly aid navigational performance during the mission. In this case, it is necessary to either deploy a large network of beacons and provide the AUV with a map of their location or provide the AUV with an existing map of the area and use geophysical methods. If neither method is possible, it is necessary to resurface and attempt to obtain a GPS fix at necessary intervals during the mission.

For missions above 100 km, the implementation of an accurate navigation system is more difficult because the best INS will be affected by significant drift over these distances. The deployment of a beacon network over such a large area is not practical and the number of landmarks used by SLAM techniques over such a large area makes techniques such as FastSLAM or constant-time SLAM necessary to reduce computation [29], [25]. In this scenario, a geophysical navigation system is the only practical way to ensure accurate navigation throughout the mission. However, the availability of suitable maps limits this approach to coastal areas and other regions that have already been extensively surveyed and the scalability of geophysical navigation systems has not been demonstrated.

A. Current Challenges

1) *A framework for using sonar navigation with existing systems*: Current AUVs make extensive use of sonar for data collection but there is clear strategy for using sonar systems to aid navigation. The operation of SLAM and particle filters has been discussed but there is no established method for using either of these methods to assist navigation over the course of an AUV mission. INS can be combined with GPS by using a KF but this is not a suitable strategy for sonar-based navigation systems because their estimates do not follow a Gaussian distribution. Without a framework for combining the estimates of these systems with the estimates of existing systems such as INS or USBL, they cannot be used to improve the navigational performance of existing AUVs. As a result, several studies have examined the use of statistical techniques to postprocess mission data but none have presented the performance of such a system when integrated into an AUV and used over the course of a simulated mission. Once such a framework is established, the difficulties of implementing these methods in a online AUV system will be reduced.
2) *Navigationally optimal routes*: To complete the mission requirements of current scientific and commercial AUV missions, AUVs must follow a path defined by the operator that is usually described as a waypoint system. Apart from rules for system failures and collision avoidance, AUVs exercise minimal autonomous mission control. If AUVs are to be used for more demanding

missions such as surveillance, port defence, MCM, or intelligent surveys, they must be able to significantly deviate from a user-defined path to complete their mission objectives. For these missions, a more sophisticated navigation system is required that can estimate its own performance for a given mission path. Without such a system, an AUV may attempt to follow a path that results in a critical loss of navigational accuracy. The estimation of future performance in a given situation for any AUV navigation system is not covered in the literature. While an estimate can be obtained readily by simulation, this is not computationally feasible during a mission. Without a correct characterization of the performance of the navigation system, the control system must use approximate limits that may underestimate the capability of the AUV.

3) *Use of local features for relative positioning and reactive control*: Maintaining a position relative to underwater features such as pipelines or harbor walls will become an increasingly important part of AUV missions. Machine vision systems for optical sensors are available but current AUV navigation systems cannot use descriptions of their surroundings for relative control, despite their ability to observe them in detail using side-scan and multibeam sonars. This is a major obstacle to operating AUVs from a harbor because they require a precise navigation system to return to a docking point after an extended survey mission outside the harbor. The advantages of operating from a harbor instead of a surface vessel are reduced cost and greater flexibility of operation since surface vessels are more limited by surface weather conditions. If AUVs are to be used for port defence, then this mode of operation will be essential for effective regular patrols.

4) *Navigation with minimal sonar use*: The problem of navigating with minimal sonar use is of limited interest for scientific missions but it is necessary for many military applications. Passive sonar arrays, optical sensors, or laser scanners are possible solutions but the range and reliability of these sensors is limited and requires the AUV to operate very close to the sea floor. The problem of determining the minimum sonar use necessary to provide sufficient accuracy for a particular mission requires a sophisticated solution that is currently not addressed in the literature. When minimal sonar use is required, the current navigation method is to use a high-quality INS combined with occasional use of a DVL. This is an open-loop system and will inevitably lead to drift over the course of the mission and limit the range of the AUV. If a geophysical map is used, then the problem becomes one of minimizing map use while minimizing the error in position. The solution to such a problem would involve graph-theoretical considerations of the mission path and map together with considerations of the maximum information obtainable from the map along a given path.

5) *Navigation using large features*: It is projected that AUVs will be used for future missions that involve close proximity to obstacles such as pipelines, piers, and manned vehicles [52]. To perform these missions, AUVs will require not only more sophisticated control systems but also more advanced navigation systems. In order to implement instructions essential to safe operation near these obstacles, the navigation system must be able to provide more detailed information about nearby features using imaging sensors such as cameras and side-scan sonars. Methods have been proposed to derive individual characteristics from small features and the classification of mine-like sea floor objects is an active area of research [53] but there exists no system to classify the larger, structured objects that are likely to be found in a busy shipping environment. Methods such as comparisons with side-scan images generated from models that have been used for small objects are unlikely to work for larger features. The appearance of large underwater features is highly dependent on the relative position of the AUV. This suggests a 3-D approach rather than a direct visual analysis. However, deriving 3-D data from conventional side-scan sonar data is problematic and requires assumptions concerning the reflectivity and acoustic characteristics of the environment [54].

B. Future Research

1) *Suitability of sonars for geophysical navigation*: Side-scan sonars produce an image of a wide swath of the sea floor while multibeam sonars target a smaller area but can produce an accurate, 3-D map of this area. Both are available on most commercial AUVs but it has not been established whether either is more suitable for use by a navigation system. While side-scan sonars have a much larger range and can potentially detect more features, it is easier to extract geophysical data from a multibeam sonar. An awareness of the relative navigational performance of these sonars in different environments will be an important factor in AUV design.

2) *Required resolution of underwater maps*: It has been established that a geophysically referenced navigation system is a realistic solution to the problem of long range, accurate AUV navigation. However, it has been shown that the performance of such a system is highly dependent on the accuracy and variation of such a map. The feasibility of using existing charts and surveys for AUV missions over large mission areas will be dependent on the detail of the available charts. While good performance has been obtained in a simulation using a high-resolution map in an area with high variation [55], the variation of performance with map resolution and variation has not been presented. A system that can provide graceful degradation of performance with resolution and variation is highly desirable.

3) *Extraction and classification of naturally occurring underwater features*: Visual inspection of bathymetric charts from side-scan sonar surveys reveals that the most easily identifiable features are ridges and channels along the sea floor. In many underwater environments, there is a contrasting lack of discrete features that are sufficiently symmetrical to be characterized as point features. While the problem of feature extraction from sonar has been investigated for structured, indoor environments where sonar returns can be classified as line features [28], bathymetric charts do not often contain a useful density of these features with the notable exception of ports and harbors. This implies that an AUV navigation system must be able to extract and classify such features in these environments.

The unstructured and variable nature of underwater sonar returns suggests the investigation of image processing techniques such as neural networks that have been used to classify noisy, partially observable features [56]. It is essential that a suitable system of deriving geophysical characteristics from sonar data is established that can be used with existing bathymetric surveys. However, there is a lack of published research into the use of these classification techniques on underwater sonar data.

4) *Use of contour alignment for navigation*: Since a large number of bathymetric charts provide depth information in contour form, the extraction and alignment of contours suggests a method of geophysical AUV navigation. A potential advantage of a contour

system over a grid-based system is a reduction in the required accuracy of the sonar sensors and the on-board map.

A method for extracting and joining contours from sonar data is described in [57] that requires postprocessing of large amounts of sonar data. The extracted contours are then aligned by minimizing a global cost function. Although this is a single-pass method, it is computationally expensive and is restricted to large datasets. A more suitable contour extraction algorithm is given in [58] that has the ability to track obscured and deformed contours by using a system of B-spline parameters and curve primitives. However, its extension to noisy sonar data suggests extensive preprocessing is necessary to achieve the performance described in the paper.

An alternative system designed explicitly for underwater navigation is proposed in [59] that uses critical points derived from bathymetric charts to aid navigation. Scale-invariant critical points are identified using partial differential equations and an EKF. Further work is needed to determine the stability computational requirements of this method. A more recent and potentially more robust approach is found in [60]. This describes how 3-D bathymetric data can be converted into contours, and then, matched to noisy data using wavelet techniques. The results are extensive and the wavelet algorithm is theoretically less sensitive to noise than gradient methods in [59]. Simulations using existing mission data could investigate whether this method is suitable for underwater navigation.

IV. Concluding Remarks

A review of the current methods and techniques used for underwater navigation has been presented along with a brief comparison of their suitability for the different missions that AUVs are required to perform. The current challenges of AUV navigation have been identified and some directions for future research based on these challenges have been suggested. It has been established that while techniques for navigation using inertial and acoustic methods are more mature than geophysical methods, the performance of these methods is fundamentally limited by their cost, range, and open-loop correction cycle over extended missions.

Advances in propulsion and energy storage technology have led to the increasing endurance of AUV methods [61]. The limiting factor in the operation of AUVs has become the accuracy of the navigation system. This prevents AUVs from undertaking long survey missions that require accurate positioning. While expensive inertial and acoustic systems can be used to reduce the degradation of navigational accuracy over the course of an AUV mission, their use restricts the affordability and range of AUVs. Geophysical methods offer potentially cheaper and more accurate navigation by using existing maps of an AUV mission area. However, the requirement of an existing map and the difficulties of feature recognition restrict the use of these methods. The techniques required for reliable geophysical navigation have not been fully investigated and the unstructured nature of the underwater environment suggests the use of noise-resistant classifiers that can work on incomplete data, such as neural networks. These observations can be readily extended to navigation in other unstructured environments where GPS is unavailable.

The current challenge of AUV navigation is to reduce the time-dependent drift of existing navigation systems over long missions using methods that are neither expensive to deploy nor require an extensive deviation from the mission. A drastic increase in the range of existing acoustic beacon systems will solve these problems but the energy limitations and accuracies of long-range acoustic signals make this unlikely [62]. On this basis, long-range, underwater navigation must use the AUV's local environment and its accuracy will be unavoidably constrained by the suitability of the environment for navigation. Future navigational methods must address the problems of autonomous feature extraction and identification from sonar sensors that offer the best accuracy and range in the underwater environment.

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