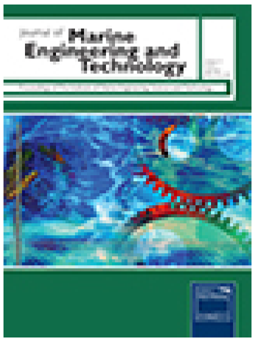


Taylor & Francis
Taylor & Francis Group

Journal of Marine Engineering & Technology

ISSN: 2046-4177 (Print) 2056-8487 (Online) Journal homepage: https://www.tandfonline.com/loi/tmar20

Review of multisensor data fusion techniques and their application to autonomous underwater vehicle navigation

D Loebis, R Sutton & J Chudley

To cite this article: D Loebis, R Sutton & J Chudley (2002) Review of multisensor data fusion techniques and their application to autonomous underwater vehicle navigation, Journal of Marine Engineering & Technology, 1:1, 3-14, DOI: 10.1080/20464177.2002.11020159

To link to this article: https://doi.org/10.1080/20464177.2002.11020159

Published online: 01 Dec 2014.

Review of multisensor data fusion techniques and their application to autonomous underwater vehicle navigation

D Loebis, R Sutton and J Chudley
Marine and Industrial Dynamic Analysis Group
Department of Mechanical and Marine Engineering
The University of Plymouth

A key problem with autonomous underwater vehicles is being able to navigate in a generally unknown environment. The available underwater sensor suites have a limited capability to cope with such a navigation problem. In practice, no single sensor in the underwater environment can provide the level of accuracy, reliability and the coverage of information necessary to perform underwater navigation. Therefore there is a need to use a number of sensors and combine their information to provide the necessary navigation capability in a synergetic manner. This may be achieved by employing multisensor data fusion (MSDF) techniques and these are the subject of the material presented in this paper.

INTRODUCTION

The oceans cover 70% of the Earth's surface and contain an abundance of living and non-living resources that remain largely untapped waiting to be discovered. However, a number of complex issues, mainly caused by the nature of underwater environments, make exploration and protection of these resources difficult to perform. In the past few decades, various world-wide research and development activities in underwater robotic systems have increased in order to meet this challenge. One class of these systems is tethered and remotely operated and referred to as remotely operated vehicles (ROVs). Extensive use of ROVs is currently limited to a few applications because of very high operational costs and the need for human presence in conducting a mission. The demand for a more sophisticated underwater robotic technology that minimises the cost and eliminates the need for human operator and is therefore capable of operating autonomously, becomes apparent. These requirements led to the development of autonomous underwater vehicles (AUVs).

To achieve truly autonomous behaviour, an AUV must be able to navigate accurately within an area of operation. In order to achieve this, an AUV needs to employ a navigation sensor with a high level of accuracy and reliability. However, in practice, as will be discussed in the next section, a single sensor alone may not be sufficient to provide an accurate and reliable navigation system, as it can only operate efficiently under certain conditions or it has inherent limitations when operating in underwater environments. It is therefore necessary to use a number of sensors and combine their information to provide the necessary navigation capability. To achieve this, a multisensor data fusion (MSDF) approach, which combines data from multiple sensors and related information from associated databases, can be used.

The aim of this paper is to survey previous work and recent development in AUV navigation and to introduce MSDF techniques as a means of improving the AUV's navigation capability. The structure of this paper is as follows: the next section describes the navigation systems that are currently being used in AUVs. MSDF is then discussed, whilst MSDF using specific sensor combinations applied to the navigation of AUVs follow.

AUTONOMOUS UNDERWATER VEHICLE NAVIGATION

Navigation systems used by AUVs that are discussed here include dead reckoning, radio, optical, acoustic and terrain-relative navigation.

Dead Reckoning Navigation

Dead reckoning is a mathematical means to determine position estimates when the vehicle starts from a known point and moves at known velocities. The present position is equal to the time integral of the velocity. Measurement of the vector velocity components of the vehicle is usually accomplished with a compass (to obtain direction) and a water speed sensor (to obtain magnitude). The principal problem is that the presence of an ocean current can add a velocity component to the vehicle, which is not detected by the speed sensor.

An inertial navigation system (INS) is a dead reckoning technique that obtains position estimates by integrating the signal from an accelerometer, which measures the vehicle's acceleration. The vehicle position is obtained in principle by double integration of the acceleration. The orientation of the accelerometer is governed by means of a gyroscope, which maintains either a fixed or turning position as prescribed by some steering function. The orientation may also, in principle, be determined by integration of the angular rates of the gyroscope. Both the accelerometer and the gyroscope depend on inertia for their operation

A dead reckoning navigation system is attractive mainly because it uses sensors that are self-contained and able to provide fast dynamic measurements. Unfortunately in practice, this integration leads to unbounded growth in position error with time due to the noise associated with the measurement and the nonlinearity of the sensors, and there is no built-in method for reducing this error. Depending on the sensors used and the specific vehicle mission, the navigational error can grow rapidly to the point where either the mission will not produce useful data or it will not be achievable at all.

Two types of dead reckoning sensors have been widely employed in AUVs: inertial measurements units (IMUs) and Doppler velocity sonar (DVS). Many very accurate IMUs have been developed for submarines. However, these are typically very expensive devices and are used only in naval vehicles. Lower cost IMUs have been used in AUVs[1]. However, due to the low acceleration encountered in autonomous underwater vehicles, these units are not normally of sufficient accuracy to provide stand-alone navigation.

DVS sensors provide measurement of a velocity vector with respect to the sea floor. These sensors normally comprise three or more separate sound beams allowing construction of a full three-dimensional velocity vector. Typically, these instruments have specifications of about 1% of the distance travelled[2]. However, these results can only be achieved when the speed of sound in the AUVs area of operation does not vary significantly as a result of changes in the salinity, temperature and density of the water. Therefore, as in the IMU case, these units are not normally used to provide stand-alone navigation.

Radio Navigation

Radio navigation systems mainly use the global positioning system (GPS)[3]. The GPS is a satellite-based navigational system that provides the most accurate open ocean navigation available. GPS consists of a constellation of 24 satellites that orbit the earth in 12 hours. There are six orbital planes (with nominally four satellites in each) equally spaced (60 degrees apart) and inclined at about 55 degrees with respect to the equatorial plane[3]. This constellation provides the user with between five and eight satellites visible from any point on the earth.

The GPS-based navigation system is used extensively in surface vessels as these vehicles can directly receive signals radiated by the GPS. Unfortunately, these signals have a limited water-penetrating capability. Therefore to receive the signals, an antenna associated with an AUV employing a GPS system must be clear and free of water. There are three possible antenna configurations to meet this requirement. These are fixed, retractable, or expendable antennas[4]. A fixed antenna is a non-moving antenna placed on the outside of the AUV. The AUV has to surface to expose this antenna and stay surfaced until the required information has been received and processed adequately. A retractable antenna is one that the AUV would deploy while still submerged. When the required information is received, the antenna is retracted back to the AUV. The expendable antenna works along the same principle as the retractable antenna, except that it is used once and discarded. When required, another antenna would be deployed.

These antenna configurations require the AUV either to surface or to rise to a shallow depth, but there are several disadvantages[5]. For an AUV to receive radio signals, it must interrupt its mission, expend time and energy climbing and/or surfacing, risk its safety for up to a minute on the surface or in a shallow depth of water getting the fix, which is especially dangerous in a hostile environment, then expend additional time and energy submerging to resume the mission. Even if an extremely accurate fix is obtained, the vehicle location uncertainty can grow significantly during descent before the mission is ever resumed. Therefore there is a need to combine information obtained by a GPS navigation system with other underwater navigation sensors when the AUV operates underwater to maintain good navigation capability.

Optical Navigation

In the context of optical imaging for navigation, the underwater environment is a very special place. The reason for this is that, in addition to visual-sensing issues that must be addressed in land and space-based vehicles, there are also issues specific to underwater imaging. These issues include limited range of visibility, brightness and contrast variation, and non-uniform illumination[6]. Limited range of visibility is caused by the attenuation of light in water by absorption and scattering by suspended matter. Light absorption and scattering cause the amount of reflected light to exponentially decay as a function of distance to scene surfaces. The absorption and scattering of light also affect image brightness and contrast. Objects far away appear dark; as they move nearer, their brightness and contrast increase. Changes in image intensity brightness and contrast can cause many image processing techniques to fail. If some type of intensity normalisation is not performed, brightness and contrast differences between images make it difficult to realise that the same scenery or object is being viewed[6]. Non-uniform illumination refers to the limitation of artificial light sources to provide uniform illumination of the entire scene under observation. A classic example that demonstrates the difficulties non-uniform lighting can cause is the imaging of a planar, perpendicular surface using a collocated camera/light source. In this case, the image centre will appear brighter than the image border. If the camera and light source are moved relative to the scene, both the absolute and relative brightness of each pixel in the image will change. Simple effects such as these can degrade correspondence (image matching) performance; more complicated effects such as shadowing can cause significant difficulties for most image correspondence techniques[6].

Optical-based navigation involves the estimation of 3D motion from time varying imagery[7,8]. Most techniques for this purpose require knowledge of relevant 2D geometric information in an image sequence. The current state-of-the-art in optical-based navigation is essentially a form of dead reckoning[9]. This method works by creating a mosaic where a series of images are taken from a video stream and aligned with each other to form a chain of images along the vehicle path. When a new image is about to be added to a mosaic, it must be properly aligned with the last image in the chain of images comprising the mosaic. To accomplish this, the two images are compared, and the displacement vector between the two image centres is calculated. Therefore, to determine the current vehicle position, it would be possible to compute the total distance travelled by summing the image displacement measurements along the image chain[9]. As with the INS discussed earlier, this method has a fundamental problem: the unbounded propagation of errors on vehicle position over time. This random walk-effect is due to the accumulation of image alignment errors as the length of mosaic increases (Fig 1). Therefore, as in the INS case, this navigation method is not normally used to provide stand-alone navigation.

Acoustic Navigation

Acoustic navigation is the most widely accepted form of AUV navigation, and a variety of systems have been both researched and tested. Most require an engineered environment, meaning that something has been added to the environment to aid navigation. The distance between acoustic baselines is generally used to define an acoustic positioning system, that is the distance between the active sensing elements. Three types of system have been primarily employed; ultra short baseline (USBL), short baseline (SBL) and long baseline (LBL) with distance between acoustic baselines less than 10 cm, between 20 to 50m and between 100 to 6000m respectively[10].

USBL systems (Fig 2a) employ a single beacon on the bottom of the seafloor which emits acoustic pulses without being interrogated from an AUV. The onboard AUV equipment consists of a two-dimensional hydrophone array mounted on the bottom of the AUV. USBL systems measure the time- or phase difference of the arrival of an acoustic pulse between individual elements of the hydrophones. This time- or phase difference is used to determine the bearing from the USBL transceiver to the beacon. If a time-of-flight interrogation technique is used, a range to that beacon will also be available from the USBL system. In SBL (Fig 2b) three or more transceivers are rigidly mounted on the hull of the AUV, making either an equilateral or a right-angled triangle. The distance between each transceiver is precisely known. A bearing to the transponder is derived from the detection of the relative time-of-arrival as an acoustic pulse passes each of the transceivers. If the time-of-flight interrogation technique is used, a range to that beacon will also be available from the SBL system. Any range and bearing position derived from USBL and SBL systems are with respect to the transceivers mounted on the AUV and, as such, the systems need a vertical reference unit (VRU), a gyroscope and, possibly, a surface navigation system to provide a position that is seafloor (Earth) referenced[10].

In LBL navigation systems (Fig 2c), an array of acoustic beacons separated by a range of 100m to a few kilometres is deployed on the seabed[10,11]. The vehicle determines its position by listening to the pulses emitted from the beacons and recording the arrival times. The location of these beacons must be provided, and the vehicle must be able to detect and distinguish between their signals. The two major types of LBL navigation are described as spherical and hyperbolic. In spherical navigation, the vehicle interrogates the array by emitting its own pulse and then listens for the responses from the beacons. In hyperbolic LBL navigation, the vehicle does not interrogate the array, but instead listens passively to the synchronised pulses emitted by the beacons[12]. Any range/range position derived from a LBL system is with respect to relative or absolute seafloor co-ordinates. As such a LBL system does not require a VRU or gyroscope[10].

Terrain-Relative Navigation

For some applications of AUVs, the use of acoustic beacons is undesirable or impractical. In particular, the acoustic beacons must be pre-deployed for every mission and the vehicles can operate only over relatively short ranges, and they are far too expensive to be practical in low cost civilian AUV work. Also the accuracy of the acoustic signals tend to degrade due to noise and reverberation problem. This then motivates the use of onboard terrain sensors for the purpose of navigation of an AUV. An onboard sensor is used to obtain information on the terrain surrounding the vehicle in the form of features or landmarks. The vehicle maintains a map of these landmarks which may or may not have been provided a priori. As the vehicle moves through the environment, the landmark observations obtained from the terrain sensor are matched to the landmarks maintained in the map and used, in much the same way as beacon observations, to correct and update the estimated location of the vehicle. In underwater environments it is very rare that an a priori terrain map will exist. Unlike surface applications, satellite or aircraft imagery cannot be used to build an underwater terrain map. This then precludes the common use of digital terrain elevation data (DTED) as employed by systems such as terrain contour matching (TERCOM) used for cruise missiles[13]. This limitation then motivates the development of simultaneous localisation and mapping (SLAM) for AUV navigation (see Fig 3).

SLAM is the process of concurrently building a feature-based map of the environment and using this map to obtain estimates of the location of the vehicle. In essence, the vehicle relies heavily on its ability to extract useful navigation information from the data returned by its sensors. The vehicle typically starts at an unknown location with no a priori knowledge of landmark locations. From relative observations of landmarks, it simultaneously computes an estimate of vehicle location and an estimate of landmark locations. While continuing in motion, the vehicle builds a complete map of the landmarks and uses these to provide continuous estimates of the vehicle location. By tracking the relative position between the vehicle and identifiable features in the environment, both the position of the vehicle and the position of the features can be estimated simultaneously. The SLAM algorithm has recently seen a considerable amount of interest from AUV community as a tool to enable fully autonomous navigation[14,15,16].

MULTISENSOR DATA FUSION

It is clear from the previous discussion that information from sensors used in one navigation system need to be combined or fused with information from sensors of other navigation systems to improve the overall accuracy of the system. To achieve this, MSDF techniques, which combine data from multiple sensors and related information from associated databases can be used[17,18]. Varshney[19] describes MSDF as the acquisition, processing and synergistic combination of information gathered by various knowledge sources and sensors to provide a better understanding of a phenomenon. In this section, a general introduction to MSDF is provided. The description on benefits of MSDF, problems and issues, levels of MSDF where fusion takes place and MSDF algorithms are presented.

Benefits of MSDF

In general, fusion of multisensor data provides significant advantages over single source data. The advantages can be summarised as follows[19,20]:

1. *Improved system reliability and robustness*. Multiple sensors have inherent redundancy. Due to the availability of data from multiple sensors, uncertainty can be reduced, noise can be rejected and sensor failure can be tolerated.

2. *Extended coverage*. An increase in both spatial and temporal coverage of an observation is made possible by the use of multiple sensor systems. Multiple sensors can observe a region larger than the one observable by a single sensor.

3. *Increased confidence*. Joint data from multiple sensors confirm the set of hypotheses about an object or event. The confirmation can be used to exclude some hypotheses to produce a reduced set of feasible options and as a result reduce the effort required to search for the best solution.

4. *Enhanced resolution*. Multiple sensors with different resolution can result in a greater resolution than a single sensor can achieve.

Problems and Issues

A technique for MSDF should consider several key issues, summarised below[19,20]:

1. *Registration/data alignment*. Each sensor provides data in its local frame. The data from different sensors must be converted into a common reference frame before combination. This problem of aligning sensor reference frames is often referred to as a registration problem.

2. *Correspondence/data association*. Once the sensors are registered, there is still a need to establish which data features in one sensor refer to the same aspect environment of the sensor.

3. *Fusion*. The fusion of data from multiple sensors or a single sensor over time can take place at different levels of representation. A useful categorisation is to consider MSDF as taking place at signal-, pixel-, feature- and symbol levels of representation.

4. *Inference and estimation*. Once the data has been fused, it is necessary to infer the sensed data due to the inherent uncertainty in the combined measurements.

5. *Sensor Management*. Sensor management can take the form of active data gathering where the sensors are directed via feedback to specific fusion stage, physical reconfiguration of the spatial pattern of the sensors and sensor type, or algorithmic changes to the combination of data.

Levels of MSDF

The common fused representation may range from a low-level probability distribution for statistical inference to high level logical proposition used in production rules for logical inference. Luo and Kay[22] and Luo et al [23] divide the levels of representation of MSDF into signal-, pixel-, feature- and symbol levels.

1. *Signal-level*. Signal-level fusion deals with the combination of signals from a group of similar sensors with the aim of deriving a single composite signal, usually of the same form as the original signals but with a higher quality. The signals produced by the sensors can be modelled as random variables corrupted by uncorrelated noise, with the fusion process considered as an estimation procedure. A high degree of spatial and temporal registration between the sensed data is necessary for fusion to take place.

2. *Pixel-level*. Pixel-level fusion deals with the combination of multiple images into a single image with a greater information content. The fused images can be modelled as a realisation of a stochastic process across the image, with the fusion process considered as an estimation procedure. In order for pixel-level to be feasible, the data provided by each sensor must be able to be registered at the pixel-level and, in most cases, must be sufficiently similar in terms of its resolution and information content.

3. *Feature-level*. Feature-level fusion deals with the combination of features derived from signals and images into meaningful internal representations or more reliable features. A feature provides for data abstraction and is created either through the attachment of some type of semantic meaning to the results of the processing of some spatial and/or temporal segment of the sensory data or through a combination of existing features. As compared to the signal- and pixel-level fusion, the sensor registration requirements for feature-level fusion are less stringent, with the result that the sensors can be distributed across different platform.

4. *Symbol-level*. Symbol-level fusion deals with the combination of symbols with an associated uncertainty measure, each representing some decision, into symbols representing composite decisions. A symbol derived from sensory information represents a decision that has been made concerning some aspect of the environment. The decision is usually made by matching features derived from the sensory information to a model. The sensor registration is usually not explicitly considered in symbol-level fusion because the spatial and temporal extent of the sensory information upon which a symbol is based has already been explicitly considered in the generation of the symbol.

MSDF Algorithms

This section presents fusion algorithms for MSDF. Luo et al[23] classify MSDF algorithms as follows: estimation methods, classification methods, inference methods and artificial intelligence methods. Each of these methods will be discussed here and applications to AUV navigation are presented later.

1. *Estimation methods*. A general estimation method of fusion is to take a weighted average of redundant information provided by a group of sensors and use this as the fused value. While this method provides real-time processing capability of dynamic low-level data, the Kalman filter is generally preferred as it provides a method that is nearly equal in processing requirement and results in estimates for the fused data that are optimal in a statistical sense. Kalman filtering is an estimation method that combines all available measurement data, plus prior knowledge about the system and measuring devices, to produce an estimate of the state in such a manner as to minimise the error statistically[24]. A detailed formulation of Kalman filter is given in

appendix A.

2. Classification methods. Classification methods involve partitioning of the multidimensional feature space (by geometrical or statistical boundaries) into distinct regions, each representing an identity class. In this method, the location of a feature vector to prespecified locations in feature space is compared. A similarity measure must be computed and each observation is compared to a priori classes. In the cluster analysis approach, geometrical relationships on a set of sample data in a training process are established[25]. Other approaches include unsupervised or self-organised learning algorithms such as K-means clustering and the associated adaptive update rule, the Kohonen feature map[26]. To fuse sensory data in an adaptive manner and allow to automatically adjust the granularity of the classifier and to maintain stability against category proliferation in the presence of drifting inputs and changing environments, ART, ARTMAP and Fuzzy ART network approaches can be used.

3. Inference methods. Bayesian inference and Dempster-Shafer evidential reasoning are the main approaches in inference methods. Bayesian inference provides formalism for MSDF that allows sensory data to be fused according to the rules of probability theory. This approach relies on the use of Bayes' rule where a relationship between the a priori probability of a hypothesis, the conditional probability of an observation given a hypothesis and the a posteriori probability of the hypothesis is provided[18]. An immediate problem in this approach is that the required knowledge of the a priori probability and the conditional probability may not be always available. Also in defining these probabilities, often subjective judgements are necessary[27]. An extension to the Bayesian inference method, Dempster-Shafer evidential reasoning, overcomes these drawbacks by keeping track of an explicit probabilistic measure of the lack of information concerning a proposition's probability. The cost of this approach is the additional time required for computation.

4. Artificial intelligence methods. Artificial intelligence is a vast, loosely defined area encompassing various aspects of pattern recognition and image processing, natural language and speech processing, automated reasoning and a host of other disciplines. Fuzzy logic and neural network are two of the most widely used approaches in artificial intelligence methods for combining multisensor data. Fuzzy logic involves extension of Boolean set theory and Boolean logic to a continuous-valued logic via the concept of membership functions to quantify imprecise concepts. Neural network is a method designed to mimic a theory of how biological nervous systems work. In this method, an individual neuron takes weighted input from a number of sources, perform a simple function and then produces a single output when the required threshold is reached. Neurons can be trained to represent sensor data and, through associate recall, complex combinations of the neurons can be activated in response to different sensor stimuli[23].

APPLICATIONS OF MULTISENSOR DATA FUSION

The discussion here focuses on a variety of approaches to the fusion of information from combinations of different types of sensors.

Inertial and GPS-Based Systems

McGhee et al[28] describe a navigation system employed by the *Phoenix* AUV using an inertial and differential GPS (DGPS) navigational suite to conduct shallow-water mine-detection and coastal environment monitoring missions. In the course of its mission, *Phoenix* combines signal-level information from a gyroscope, depth sensor, speed sensor, and a compass heading to predict its position while operating underwater. The vehicle surfaces periodically to obtain an update of its position from a DGPS fix and then submerges (Fig 4a). Problems with this setup concern the time required to acquire the DGPS data and the influence of water covering the DGPS antenna during position fixing were examined in Norton[29]. The inertial navigation sensors described in McGhee et al[28] obtain accelerations and angular rates of change for the vehicle. A 'nine state' Kalman filter is used to process the data and to give the prediction of the vehicle position. The DGPS data is then used to update the predicted position resulting in an estimated position. The nine state Kalman filter can be divided into seven continuous-time states (three Euler angles, two horizontal velocities, and two horizontal positions) and two discrete-time states (estimated east and north current derived from the DGPS fixes). The method used to fuse sensory information discussed by McGhee et al[28] can be shown as in Fig 4b.

The main problem with the Kalman filter employed in McGhee et al[28] is the need for a tuning system to prevent filter divergence. This problem can be overcome by the use of artificial intelligence (AI) techniques as have been applied in helicopters[30], automobiles[31] and target tracking system[32] applications. Kobayashi et al[31] wished to determine accurately the position of an automobile using DGPS. In their work, a fixed fuzzy rule based algorithm is used to tune the covariance factors of a Kalman filter. The shape and positioning of the various fuzzy sets on their respective universes of discourse having been decided by heuristic means. The main problem with the Kobayashi et al[31] methodology is the reliance on trial and error to generate the fuzzy rule based algorithms. Similar comments can also be made concerning the robot positioning work of Jetto et al[33]. To overcome such drawbacks genetic algorithms[34,35] have been used to optimise fuzzy systems. Other intelligent optimisation techniques such as chemotaxis, alopex and simulated annealing have also been successfully employed in the design optimisation of fuzzy control systems[36,37].

Acoustic-Based Systems

Atwood et al[38] have built and tested an AUV that utilises a LBL navigation system with an innovative fix-finding algorithm and commercially-available hardware. They use a spherical navigation system, in which the vehicle actively interrogates acoustic transponders and calculates ranges from round trip transit times, resulting in a greater accuracy (about 1m) compared to the hyperbolic method proposed by Bellingham et al[12]. In this system, the vehicle can use two operating modes, master mode and transponder mode. In the first mode, the vehicle triggers the acoustic transponders, which reply with an acoustic signal. The vehicle computer can then calculate distances and, applying acoustically measured depth, a position. Using the first mode, operation over an area of 1 km^2 is possible. In the second operating mode, a surface vessel triggers the vehicle, which in turn interrogates the transponders. Position of the AUV can then be calculated in the surface vessel through an established GPS position and knowledge of the relative positions of the AUV and the transponders. This procedure is called the *fish solution*, as it lets the operator on the ship monitor vehicle progress. The second mode is developed to have operational areas as large as 10 km^2.

In this work, Atwood et al[38] have solved the problem of fading or destructive interference of the acoustic signals produced by the transponders encountered by Bellingham et al[39]. Atwood et al[38] principally combine sensor information at signal-level data.

Rendas and Lourtie[40] combine LBL navigation with dead reckoning and calls it a *hybrid system*. The vehicle travels between deployed baseline arrays, each consisting, for example, of four transponders, and uses acoustic navigation when in range of an array. Outside the range, it uses a sonar/Doppler sensor and depth information for autonomous navigation. The distances between the arrays must be carefully planned, because the accuracy of navigation in the autonomous mode deteriorates with time, depending on the quality of the sensing systems. The transition from one mode to another takes place automatically. When the vehicle is leaving the area where a particular baseline array is located, the number of range measurements it is able to receive will gradually decrease to zero, entering, in this way, the autonomous navigation mode. On the contrary, when it approaches an area where transponders are located, it receives an increasing number of distance measurements, switching from autonomous to local navigation mode. The system uses a variable dimension Kalman filter for both navigation modes. Where there is no detectable acceleration, the filter assumes uniform motion and estimates position and linear velocity. When there is acceleration, the filter switches to a larger order (manoeuvring model) and extends its state vector to include the accelerations. In this work, however, Rendas and Lourtie[40] have not taken into account the analytical approximations to the error evolution during autonomous navigation to determine the layout of the baseline arrays and to derive the constraints on path planning once a layout has been decided upon. Similar to Bellingham et al[38], the MSDF method used by Rendas and Lourtie[40] is an estimation method which fuses data from the navigation sensors at signal-level.

Acoustic- and Optical-Based Systems

Majumder et al[14,15,16] reported the use of sonar and underwater cameras to construct a complete environmental map for navigation. A generic, multi-layered data fusion scheme is used to combine information from the two sensors. The general principle is that all sensor information is projected into a common state-space before the extraction of seabed features. Once projection has occurred, feature extraction and subsequent processing is based on a combined description of the environment. As robust features, such as points and lines turn out to be fragile in a natural underwater environment, Majumder et al found that this approach is better than extracting features from a single piece of sensor information followed by fusion. In this work, 'blobs' and blob-like patches are used as scene descriptors to segregate feature information from background noise and other errors. Majumder et al discussed both the Bayesian and extended Kalman filter (EKF) approaches to map-building and localisation in autonomous navigation systems. It was shown in this work that a significant problem in applying EKF is the difficulty of modelling natural environment features in a form that can be used in an EKF algorithm. Another formidable problem is the fragility of the EKF method when faced with incorrect associations of observations to landmarks. The limitations in using EKF to build a feature map of landmarks describing the environment were then resolved through the use of the Bayesian approach. The fusion process can be shown as in Fig 5. A significant problem with this approach lies on the stability of the algorithm when the vehicle is run over long distances and returning around a loop to the initial vehicle location. This problem stems from the limitation in data association technique to correspond initially identified landmarks and the same landmarks viewed from the opposite side on the return visit. A potential solution to this problem is to use a probabilistic model to provide a very general description of landmarks form and shape.

Twin Burger 2, an AUV developed by the University of Tokyo, was designed to help monitor and carry out routine maintenance work of underwater cables[41,42]. In doing so, the vehicle tracks the cable visually and provides human operators with visual information about the condition of the cable accordingly. Initially the vehicle employed a visual servoing system to track the cable and to navigate the AUV accordingly. However, due to undesirable optical behaviour underwater, there were many occasions where the cable was not sufficiently visible for the vision processor to track the cable. In addition, the vehicle can lose track of the cable when there were many similar cables appearing in the image. In order to overcome these problems, a multisensor fusion technique is proposed. The proposed sensor fusion technique uses dead reckoning position uncertainty with a 2D-position model of the cable to predict the region of interest in the image captured by a camera mounted on the AUV[41,42]. The 2D-position model of the layout of the cable is generated by taking the position $(x_i y_i)$ of a few points along the cable. The 2D-position model of the cable is used to predict the most likely region of the cable in the image, which leads to a reduction in the amount of image data and a decrease in the image processing time. Additionally, due to the narrowing of the region of interest in the image, the chances of misinterpretation of similar features appearing in the image can be avoided. The 2D-position model is also used to generate navigation commands when the vision processor cannot recognise the cable in the environment. Similar to Majumder et al[14,15,16], the fusion process takes place at feature-level.

Scheizer[43] has reported a target detection and classification system using side scan sonar data and vision. Objects are detected by searching for highlights, textures, statistical anomalies and shadows. An artificial neural network-based classification system is used to assist the image-processing component. The classification process does not identify objects but rather labels them as foreground, background, highlight, or shadow highlight. The level of correct classification is reported to be 95% using a training set of 62 images. This technique, however, does not address the issue of feature- or object identification.

CONCLUDING REMARKS

It has been suggested in this paper, from the various examples given in AUV navigation, that information coming from a single navigation system is not sufficient to provide a good navigation capability. Therefore MSDF techniques which combine sensory information from other navigation systems to improve the navigation capability is essential. MSDF techniques which combine sensory information from inertial, radio and optical navigation system to track underwater cables is currently being developed in a three year co-operative project funded by EPSRC involving both the University of Plymouth and Cranfield University, UK. The navigation system that is being developed at the University of Plymouth utilises INS/GPS and will be enhanced by a vision-based navigation system being developed at Cranfield University.

During an underwater cable tracking mission, the position obtained by the INS will be combined with a dead reckoned position obtained from a vision-based navigation system. In addition, the 2D-position model of the cable can also be included to predict the most likely region of the cable in the image, which leads to a reduction in the amount of image data and a decrease in the image processing time as discussed in[41,42]. The vision system will be based on the laser stripe illumination methodology previously developed at Cranfield University[44], overcoming optical imaging problems such as range of visibility, brightness and contrast, and illumination of the seabed as discussed by Marks et al[6]. The combined positions are then used to identify the locations of the gathered images of the cable.

A significant improvement in accuracy of the navigation system is expected as the accumulated error using the combined INS and video-based navigation is to be minimised by the GPS update methodology as discussed by McGhee et al[28] and also as the Kalman filter will be made adaptive by using fuzzy logic techniques to prevent the filter divergence as discussed by Kobayashi et al[31].

ACKNOWLEDGEMENT

This research has been supported by the Engineering and Physical Sciences Research Council (EPSRC), QinetiQ (Winfrith and Bincleaves), J&S Marine, South West Water PLC and Halliburton Subsea.

REFERENCES

1. Cox, R, and Wei, S, (1995). *Advances in the State of the Art for AUV Inertial Sensors and Navigation Systems.* IEEE Journal of Oceanic Engineering, **20** (4), pp. 361-366.

2. Bellingham, JG. (1992). *Capabilities of Autonomous Underwater Vehicles*. In J. Moore., Editor, Scientific and Environmental Collection with Autonomous Underwater Vehicles, pp. 7-14. MIT Sea Grant.

3. Ellowitz, HI. (1992). *The Global Positioning System*. Microwave Journal, 35 (4), pp. 24-33.

4. Kwak, SH, McKeon, JB, Clynch, JR, and McGhee, RB. (1992). *Incorporation of Global Positioning System into Autonomous Underwater Vehicle Navigation*. Proceedings of the 1992 Symposium on Autonomous Underwater Vehicle Technology, Washington, DC, pp. 291-297.

5. Kwak, SH, Stevens, CD, Clynch, JR, McGhee, RB, and Whalen, RH. (1993). *An Experimental Investigation of GPS/INS Integration for Small AUV Navigation*. Proceedings of International Symposium on Unmanned Untethered Submersible Technology, Durham, NH, pp. 239-251.

6. Marks, RL, Rock, SM, and Lee, MJ. (1994). *Real-Time Video Mosaicking of the Ocean Floor.* IEEE Journal of Oceanic Engineering, **20** (3), pp. 229-241.

7. Victor, JS, and Sentieiro, J. (1994). *The Role of Vision for Underwater Vehicles*. Proceedings of the 1994 Symposium on Autonomous Underwater Technology, Cambridge, MA, pp. 28-35.

8. Hallset, JO. (1992). *A Vision System for an Autonomous Underwater Vehicle*. Proceedings of the 11th IAPR International Conference on Pattern Recognition, Los Alamitos, CA, pp. 320-323.

9. Huster, A, Fleischer, SD, and Rock, SM. (1998). *Demonstration of a Vision-Based Dead-Reckoning System for Navigation of an Underwater Vehicle*. Proceedings of the Oceans '98 MTS/IEEE, Nice, France, pp. 326-330.

10. Vickery, K. (1998). *Acoustic Positioning Systems: A Practical Overview of Current Systems*. Proceedings of the 1998 Workshop on Autonomous Underwater Vehicle, Cambridge, MA, pp. 5-17.

11. Geyer, EM, Creamer, PM, D'Appolito, JA,and Gains RG. (1987). *Characteristics and Capabilities of Navigation Systems for Unmanned Untethered Submersibles*. Proceedings International Symposium on Unmanned Unthetered Submersible Technology, Durham, NH, pp. 320-347.

12. Bellingham, JG, Consi, TR, Tedrow, U, and Di Massa, D. (1992). *Hyperbolic Acoustic Navigation for Underwater Vehicles: Implementation and Demonstration*. 1992 IEEE Symposium on Autonomous Underwater Vehicle Technology, Washington, DC, pp. 304-309.

13. Golden, JP. (1980). *Terrain Contour Matching (TERCOM): A Cruise Missile Guidance Aid*. SPIE: Image Processing for Missile Guidance, 238, pp. 10-18.

14. Majumder, S, Sheding, S, and Durrant-Whyte, HF. (2000). *Sensor Fusion and Map Building Localisation for Underwater Navigation*. Proceedings of the 7th International Symposium on Experimental Robotics, Honolulu, Hawaii.

15. Majumder, S, Scheding, S, and Durrant-Whyte, HF. (2000). *Sensor Fusion and Map Building for Underwater Navigation*. Proceedings of the Australian Conference on Robotics and Automation, Melbourne, Australia, pp. 25-30.

16. Majumder, S, Scheding, S, and Durrant-Whyte, HF. (2001). *Multisensor Data Fusion for Underwater Navigation*. Robotics and Autonomous Systems 35, pp. 97-108.

17. Llinas, J, and Waltz, E. (1990). *Multisensor Data Fusion.* Artech House: Boston, MA.

18. Hall, D. (1992). *Mathematical Techniques in Multisensor Data Fusion*. Artech House: Boston, MA.

19. Varshney, PK. (1997). *Multisensor Data Fusion*. Electronics and Communication Engineering Journal, 9 (6), pp. 245-253.

20. Harris, CJ, Bailey, A, and Dodd, TJ. (1998). *Multisensor Data Fusion in Defence and Aerospace*. The Aeronautical Journal, 102 (1015), pp. 229-241.

21. Hall, DL, and Llinas, J. (1997). *An Introduction to Multisensor Data Fusion*. Proceedings of the IEEE, 85 (1), pp.6-23.

22. Luo, RC, and Kay, MG. (1990). *A Tutorial on Multisensor Integration and Fusion*. Proceedings of 16 Annual Conference of IEEE of Industrial Electronics Society, Pacific Groove, CA, pp. 707-722.

23. Luo, RC, Chih-Chen, Y, and Kuo, LS. (2002). *Multisensor Fusion and Integration: Approaches, Application and Future Research Directions*. IEEE Sensors Journal, 2 (2), pp. 107-119.

24. Brown, P, and Hwang, P. (1997). *Introduction to Random Signals and Applied Kalman Filtering.* Wiley & Sons, Inc.: Toronto, Canada.

25. Bracio, BR, Horn, W, and Moller, DPF. *Sensor Fusion in Biomedical Systems.* (1997). Proceedings of the 19th Annual International Conference of IEEE Engineering in Medicine and Biology and Society, Chicago, IL, pp. 1387-1390.

26. Kohonen, T. (1988). *Self-Organization and Associative Memory*. Springer-Verlag: New York.

27. Brooks, RR, and Iyengar, SS. (1998). *Multisensor Fusion: Fundamentals and Applications with Software*. Prentice Hall: Upper Saddle River, NJ.

28. McGhee, RB, Clynch, JR, Healey, AJ, Kwak, SH, Brutzman, DP, Yun, XP, Norton, NA, Whalen, RH, Bachmann, ER, Gay, DL, and Schubert, WR. (1995). *An Experimental Study of an Integrated GPS/INS System for Shallow-Water AUV Navigation.* 9th International Symposium on Unmanned Unthetered Submersible Technology, Durham, NH, pp. 153-167.

29. Norton, NA. (1994). *Evaluation of Hardware and Software for a Small Autonomous Underwater Vehicle Navigation System (SANS).*

Master Thesis, Naval Postgraduate School, Monterey, California.

30. Doyle, RS, and Harris, CJ. (1996). *Multisensor Data Fusion for Helicopter Guidance Using Neurofuzzy Estimation Algorithms*. The Royal Aeronautical Society Journal, June, pp. 241-251.

31. Kobayashi, K, Cheok, KC, Watanabe, K, and Munekata, F. (1998). *Accurate Differential Global Positioning via Fuzzy Logic Kalman Filter Sensor Fusion Technique*. IEEE Transaction on IndustrialElectronics, 45 (3), pp. 510-518.

32. McGinnity, S, and Irwin, G. (1997). *Nonlinear State Estimation Using Fuzzy Local Linear Models*. International Journal of Systems Science, 28 (7), pp. 643-656.

33. Jetto,L, Longhi, S., and Vitali, D. (1999). *Localisation of a Wheeled Mobile Robot by Sensor Data Fusion Based on a Fuzzy Logic Adapted Kalman Filter*. Control Engineering Practice, 7, pp. 763-771.

34. Pham, DT, and Karaboga, D. (1991). *Optimum Design of Fuzzy Controllers Using Genetic Algorithms*. Journal of Systems Engineering, pp. 114-118.

35. Sutton, R, and Marsden, GD. (1997). *A Fuzzy Autopilot Optimised Using a Genetic Algorithm*. Journal of Navigation, 50, pp. 120-131.

36. Sutton, R, Taylor, SDH, and Roberts, GN. (1996). *Neurofuzzy Techniques Applied to a Ship Autopilot Design*. Journal of Navigation, 49, pp. 410-429.

37. Sutton, R, Taylor, SDH, and Roberts, GN. (1997). *Tuning Fuzzy Ship Autopilots Using Artificial Neural Networks*. Transaction of Institute of Measurement and Control, 19 (2), pp. 94-106.

38. Atwood, DK, Leonard, JJ, Bellingham, JG, and Moran, BA. (1995). *An Acoustic Navigation system for Multi-Vehicle Operations*. 9th International Symposium on Unmanned Unthetered Submersible Technology, Durham, NH, pp. 202-208.

39. Bellingham, JG, Goudey, CA, Consi, TR, Bales, JW, Atwood, DK, Leonard, JJ, and Chryssostomidis, (1994). *A Second Generation Survey AUV*. Proceedings of the 1994 Symposium on Autonomous Underwater Vehicle Technology, Cambridge, MA, pp. 148-155.

40. Rendas, MJ, and Lourtie, IMG. (1994). *Hybrid Navigation System for Long Range Navigation*. Proceedings of the 1994 Symposium on Autonomous Underwater Vehicle Technology, Cambridge, MA, pp. 353-359.

41. Balasuriya, BAAP, and Ura, T. (1999). *Multisensor Fusion for Autonomous Underwater Cable Tracking*. Oceans'99 MTS/IEEE, Seattle, WA, pp. 209-215.

42. Balasuriya, BAAP, and Ura, T. (1999). *Sensor Fusion Technique for Cable Following by Autonomous Underwater Vehicles*. Proceedings of the 1999 IEEE International Conference on Control Applications, Kohala Coast-Island of Hawaii, Hawaii, pp. 1779-1784.

43. Scheizer, PF, and Petlevitch, EJ. (1989). *Automatic Target Detection and Cueing System for an Autonomous Underwater Vehicle*. Proceedings 7th International Symposium Unmanned Unthetered Submersible Technology, Durham, NH, pp. 359-371.

44. Tetlow, S. and Allwood, RL. (1995). *Development and Applications of a Novel Underwater Laser Illumination System*. Underwater Technology, 21 (2), pp. 13-20.

APPENDIX A

The Kalman filter and the extended Kalman filter are the most popular tools proposed in the literature for MSDF in AUV navigation. If the AUV system can be described with a linear model and both the system and sensor error can be modelled as white Gaussian noise, a Kalman filter provides unique, statistically optimal, estimates for data of interest. In the Kalman filter formulation, the observation $z(k) \in \Re^n$ are described (or approximated) by the linear model

$$z(k+1) = H(k+1)x(k+1) + v(k+1) \tag{1}$$

where $x \in \Re^m$ is a state vector, $H \in \Re^{n \times m}$ is an observation model, and $v \in \Re^n$ is the observation noise. The state vector satisfies a linear discrete-time state transition equation

$$x(k+1) = F(k+1)x(k) + G(k+1)u(k+1) + w(k+1) \tag{2}$$

where $F \in \Re^{m \times m}$ is the system model, $G \in \Re^{m \times q}$ is the control model, $u \in \Re^q$ is a known control input, and $w \in \Re^m$ is the input noise.

Independent, zero mean and white noise processes are assumed,

$$\begin{aligned} &E[w(k)] = E[v(k)] = 0, E[w(k)w^T(j)] = Q(k)\delta_{kj}, \\ &E[v(k)v^T(j)] = R(k)\delta_{kj}, E[w(k)v^T(j)] = 0 \end{aligned} \tag{3}$$

where δ_{kj} is the Kronecker delta function $(\delta_{kj} = 0,\ k \neq j;\ \delta_{kj} = 1,\ k = j)$.

The optimal mean square error estimate of $x(k)$ given $z(1), \dots, z(j)(k \geq j)$ is

$$\hat{x}(k|j) = E[x(k)|z(1), \dots, z(j)] \tag{4}$$

and the conditional covariance matrix of $\hat{x}(k|j)$ is

$$P(k|j) = E\{[x(k) - \hat{x}(k|j)][x(k) - \hat{x}(k|j)]^T | z(1), \dots, z(j)\} \tag{5}$$

The Kalman filter algorithm provides recursively an estimate $\hat{x}(k+1|k+1)$ in terms of the previous estimate $\hat{x}(k|k)$ and the most recent observation, $z(k+1)$. It involves a cycle of *prediction* and *updating* (see ref 27).

The measurement model for the EKF is

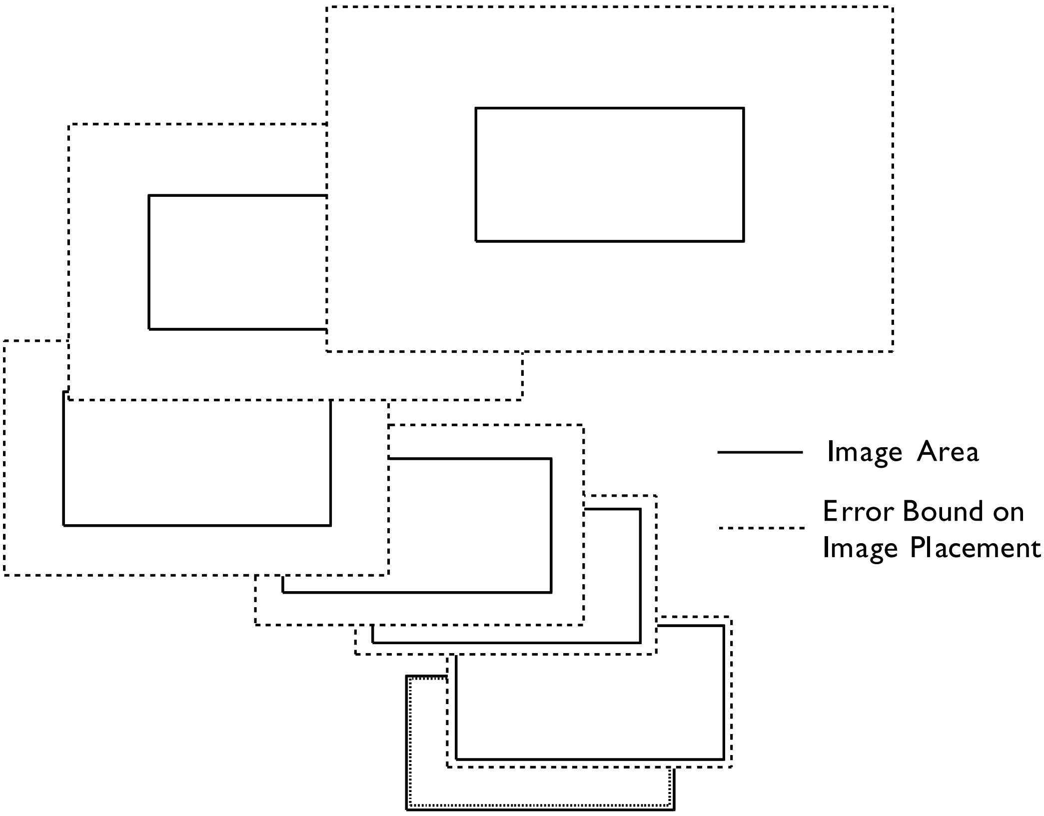
$$z(k+1) = h[k+1, x(k+1)] + v(k+1), \tag{6}$$

and the dynamics are assumed to be

$$x(k+1) = f(k+1), x(k), u(k+1) + w(k+1) \tag{7}$$

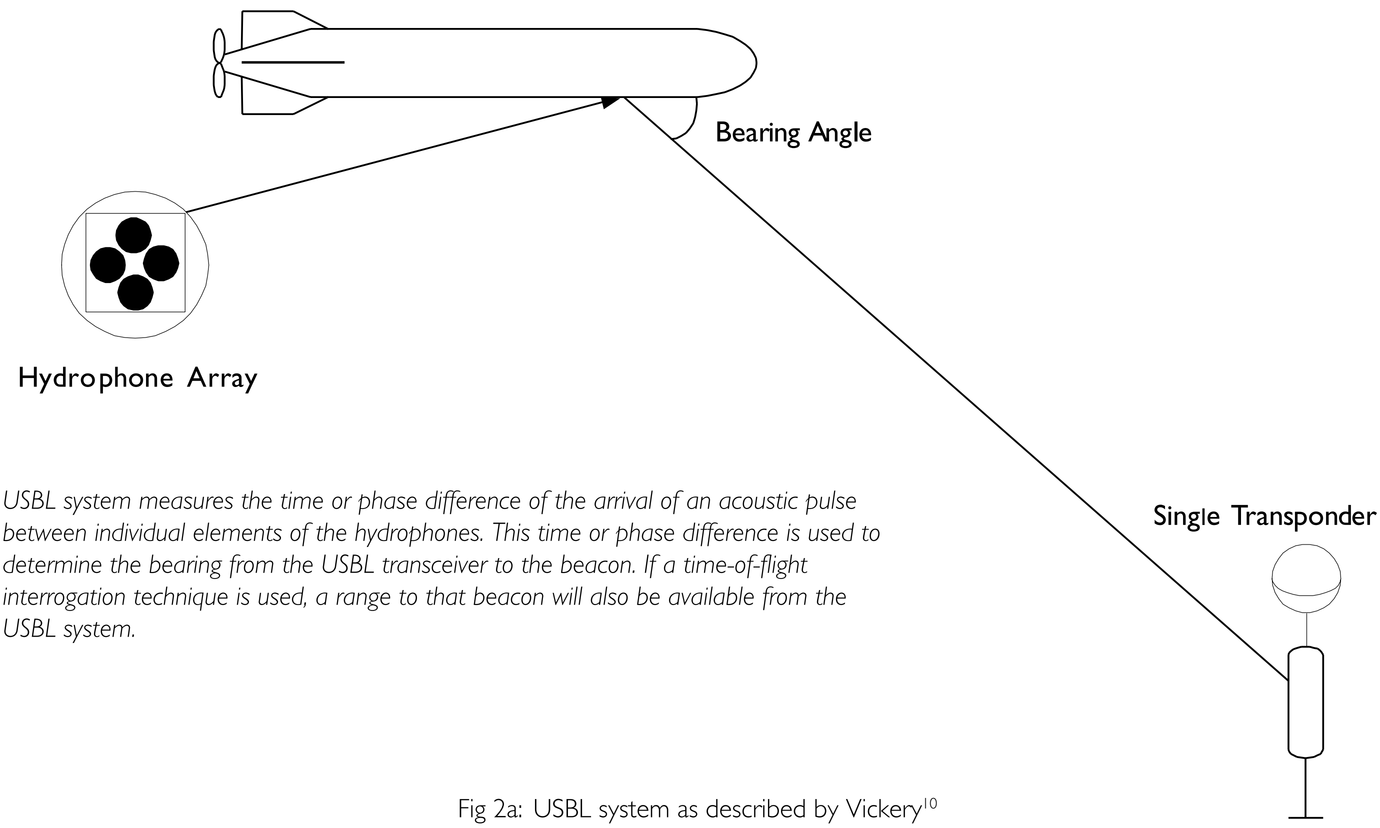
The vector-valued function h and f are, in general, time varying. The EKF framework is developed through as series expansion of the nonlinear dynamics and the measurement equation.

FIGURES



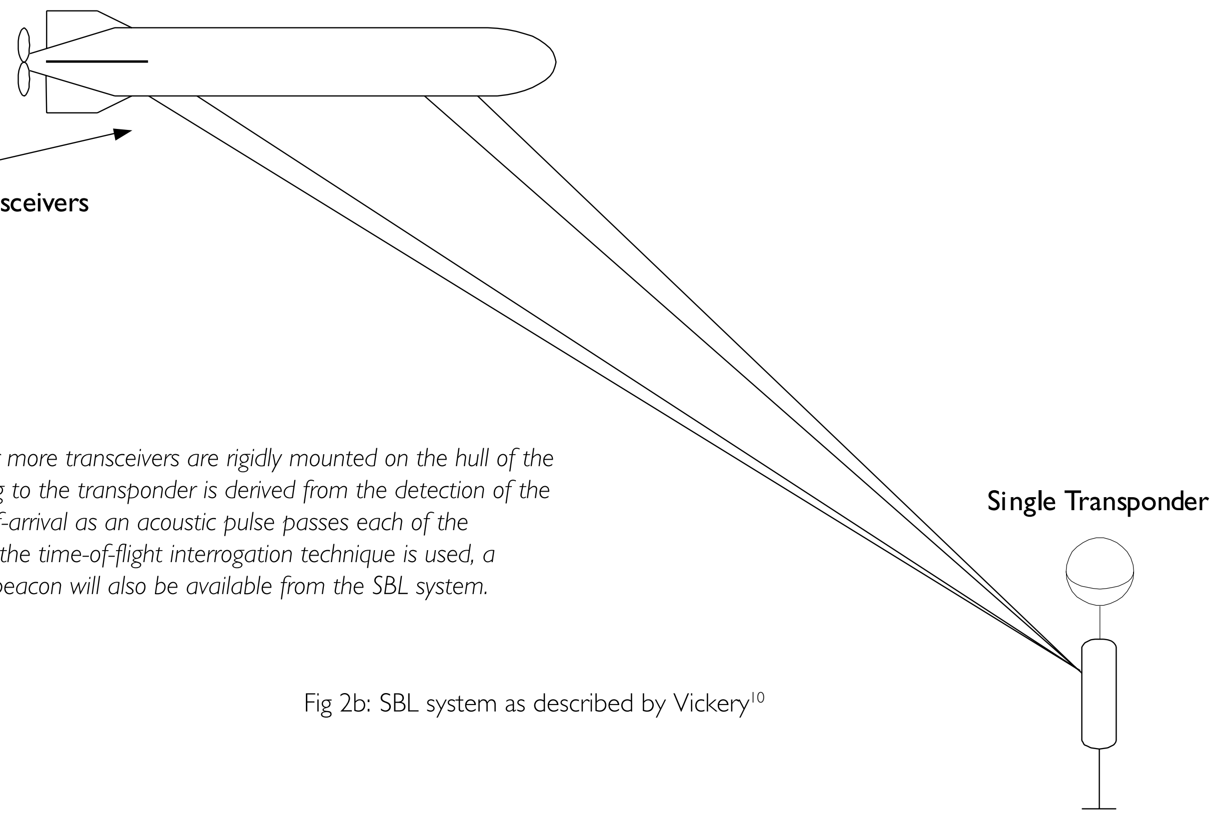
As the length of the image chain comprising the mosaic increases, the error bound in placing the last image relative to the initial image (i.e. the origin) continues to grow according to a random walk

Fig 1: Error propagation in image chain as described by Huster *et al.*[9]



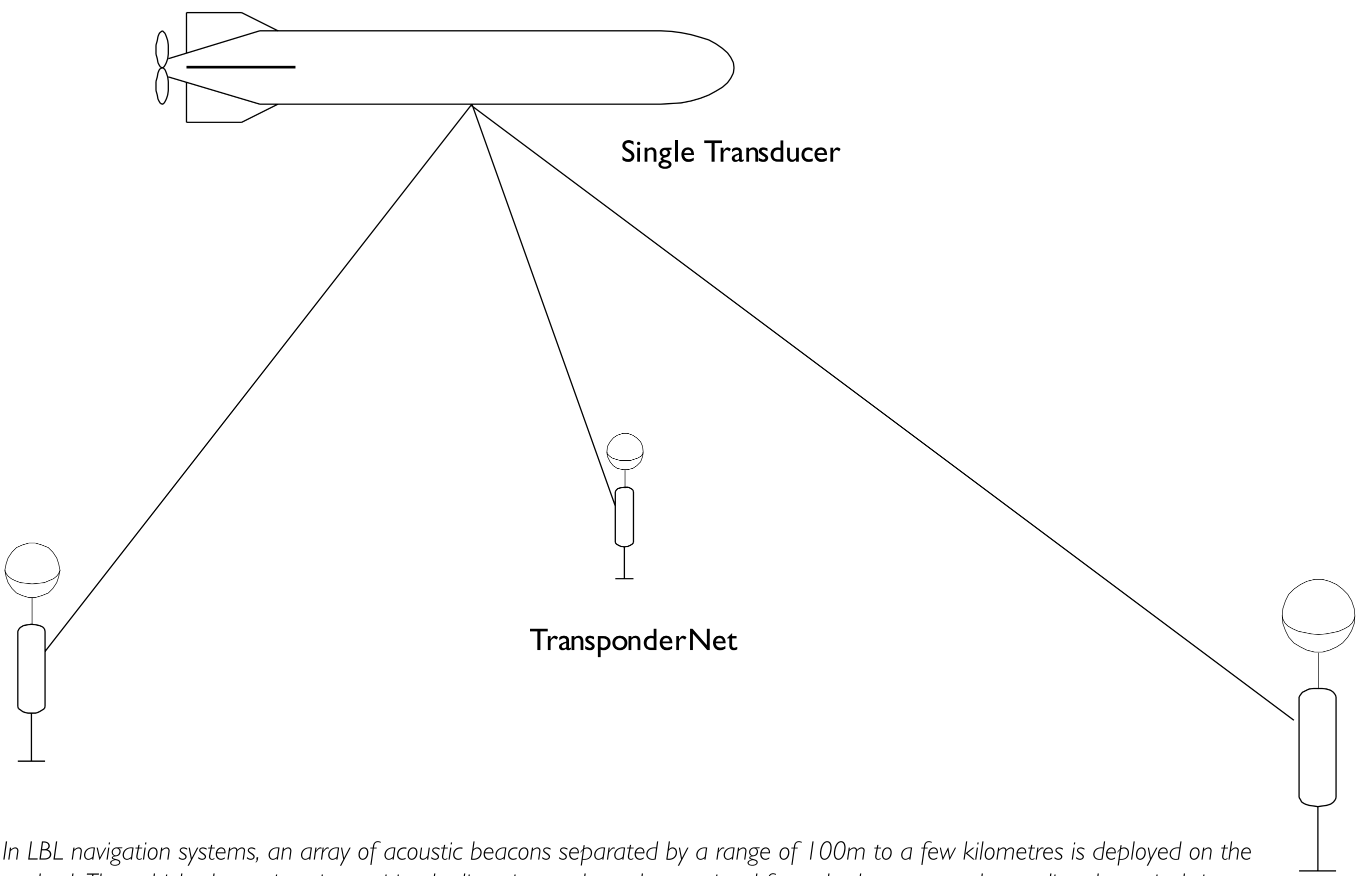
USBL system measures the time or phase difference of the arrival of an acoustic pulse between individual elements of the hydrophones. This time or phase difference is used to determine the bearing from the USBL transceiver to the beacon. If a time-of-flight interrogation technique is used, a range to that beacon will also be available from the USBL system.

Fig 2a: USBL system as described by Vickery[10]



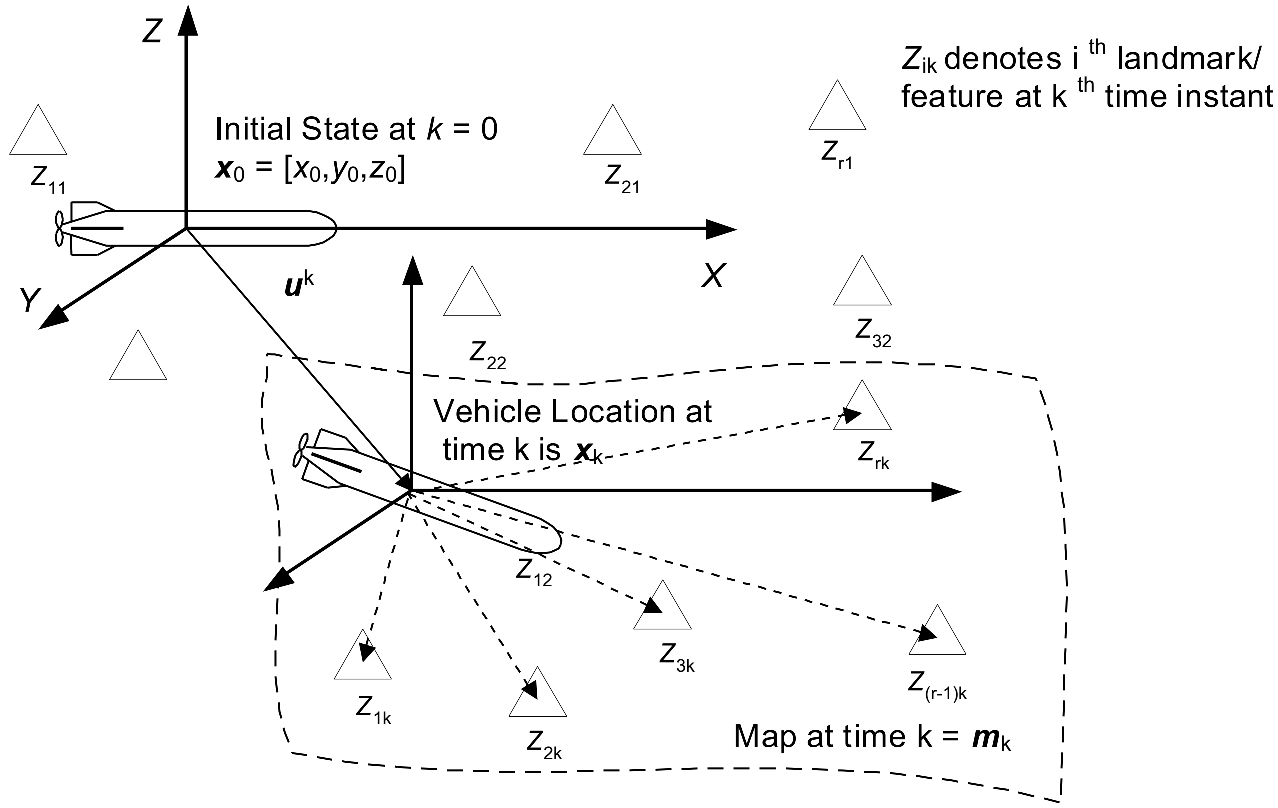
In SBL three or more transceivers are rigidly mounted on the hull of the AUV. A bearing to the transponder is derived from the detection of the relative time-of-arrival as an acoustic pulse passes each of the transceivers. If the time-of-flight interrogation technique is used, a range to that beacon will also be available from the SBL system.

Fig 2b: SBL system as described by Vickery[10]



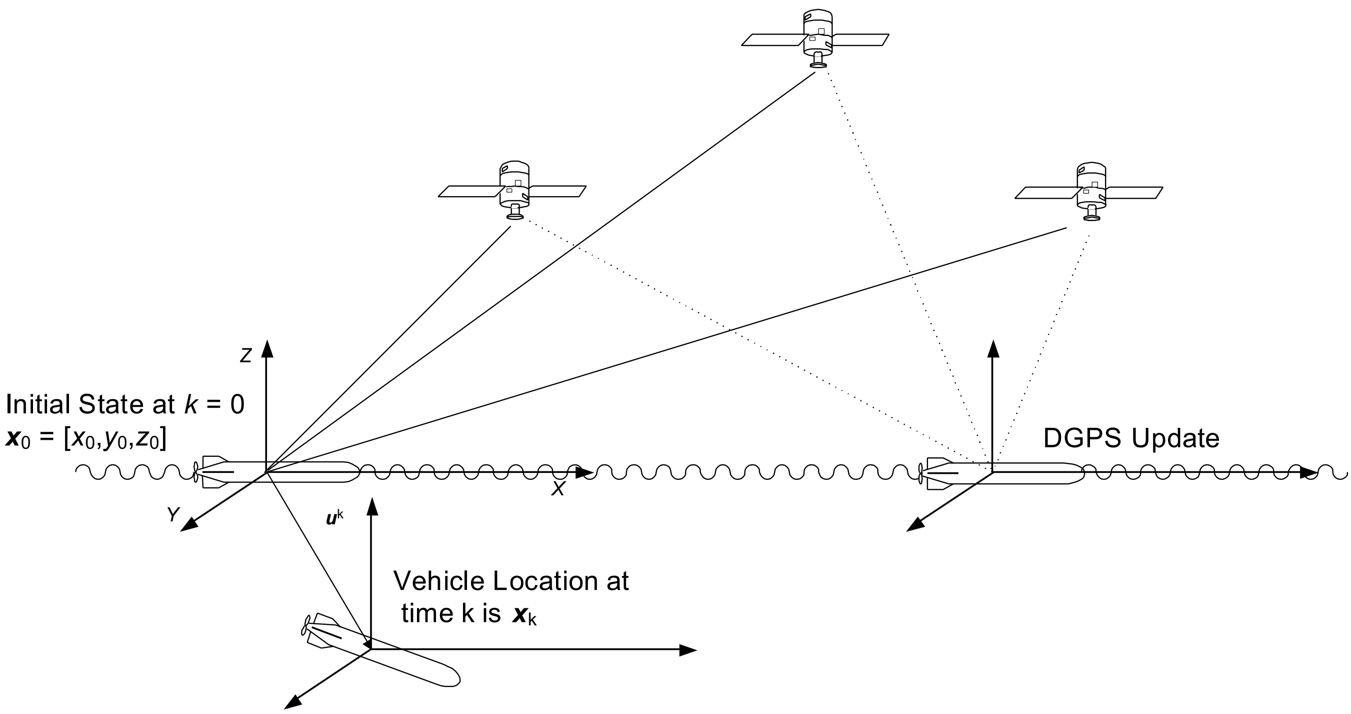
In LBL navigation systems, an array of acoustic beacons separated by a range of 100m to a few kilometres is deployed on the seabed. The vehicle determines its position by listening to the pulses emitted from the beacons and recording the arrival times.

Fig 2c: LBL system as described by Vickery[10]



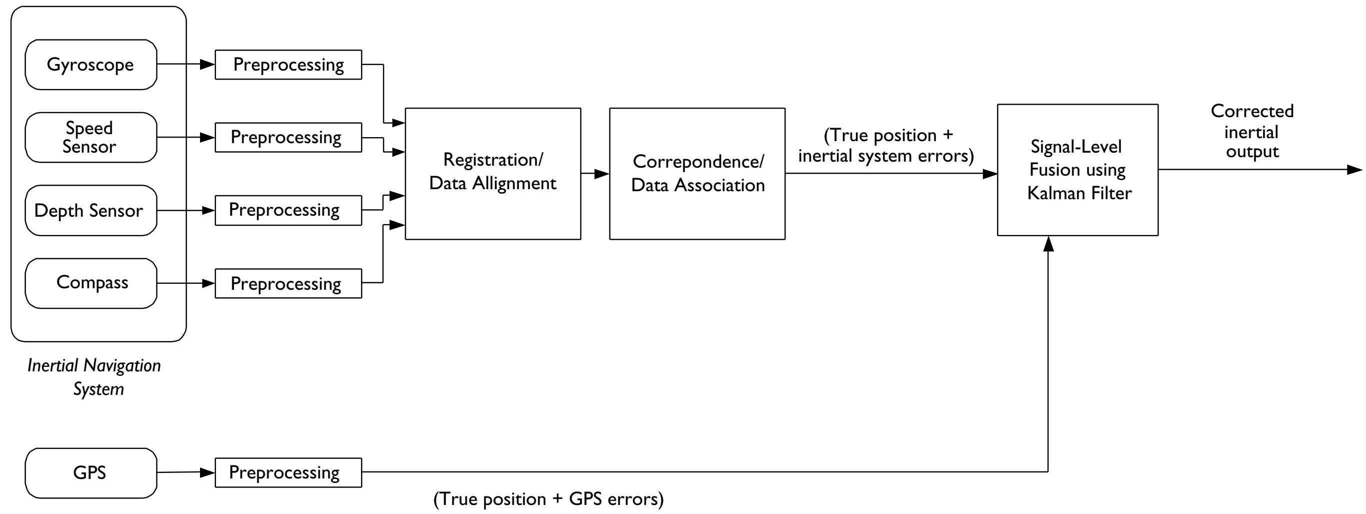
Relationship between the vehicle, features and map at any time k is shown above. Cartesian axes system is used to describe the vehicle location at any time k denoted by x_k. The vehicle states change as a result of the applied control input u_k. The map at any time k is defined as set of landmarks or features detected from the sensor observation z_k relative to the vehicle location.

Fig 3: SLAM algorithm as described by Majumder *et al.*[14,15,16]



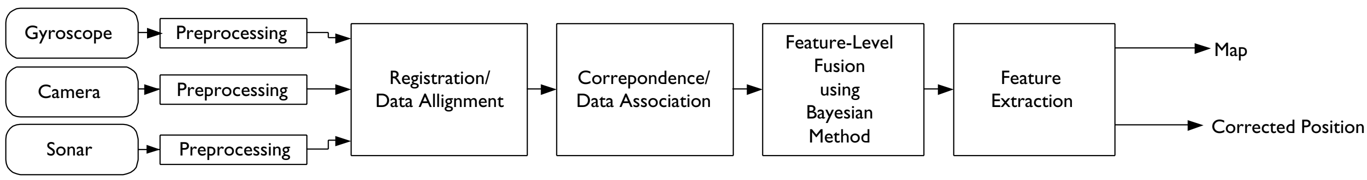
In the course of its mission Phoenix combines signal-level information INS to predict its position while operating underwater. The vehicle surfaces periodically to obtain an update of its position from a DGPS fix and then submerges.

Fig 4a: GPS/INS Navigation by McGhee *et al.*[28]



In the course of its mission Phoenix combines signal-level information from a gyroscope, depth sensor, speed sensor, and a compass heading to predict its position while operating underwater. The vehicle surfaces periodically to obtain an update of its position from a DGPS fix and then submerges to resume its mission.

Fig 4b: MSDF in GPS/INS Navigation by McGhee *et al.*[28]



The general principle is that all sensor information is projected into a common state-space before the extraction of seabed features. Once projection has occurred, feature extraction and subsequent processing is based on a combined description of the environment.

Fig 5: MSDF in SLAM algorithm as described by Majumder *et al.*[14,15,16]