Article Title Page

[Article title]
Towards Autonomous Localization and Mapping of AUVs: A Survey

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Structured Abstract:
Purpose – The main purpose of this paper is to investigate two key elements of localization and mapping of Autonomous Underwater Vehicle (AUV), i.e. to overview various sensors and algorithms used for underwater localization and mapping, and to make suggestions for future research.
Design/methodology/approach – The authors first review various sensors and algorithms used for AUVs in the terms of basic working principle, characters, their advantages and disadvantages. The statistical analysis is carried out by studying 35 AUV platforms according to the application circumstances of sensors and algorithms.
Findings – As real-world applications have different requirements and specifications, it is necessary to select the most appropriate one by balancing various factors such as accuracy, cost, size, etc. Although highly accurate localization and mapping in an underwater environment is very difficult, more and more accurate and robust navigation solutions will be achieved with the development of both sensors and algorithms.
Research limitations/implications – This paper provides an overview of the state of art underwater localisation and mapping algorithms and systems. No experiments are conducted for verification.
Practical implications – The paper will give readers a clear guideline to find suitable underwater localisation and mapping algorithms and systems for their practical applications in hand.
Social implications – There is a wide range of audiences who will benefit from reading this comprehensive survey of autonomous localisation and mapping of UAVs.
Originality/value – The paper will provide useful information and suggestions to research students, engineers and scientists who work in the field of autonomous underwater vehicles.

Keywords: AUV, Localization and mapping, Sensors, Algorithms, SLAM.

Article Classification:
Literature review

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Running Heads:

1. Introduction

For decades, Autonomous Underwater Vehicles (AUVs) have been widely used for many tasks, ranging from underwater search and rescue, mapping, climate change assessment, marine habitat monitoring, shallow water mine countermeasures, pollutant monitoring, etc. Navigation plays a significant role in the application of AUVs and consists of two fundamental aspects: localisation and mapping. Localization provides AUVs with their position and orientation information so that they can find way to go. In contrast, mapping provides AUVs with environmental information for their path planning, obstacle avoidance and goal seeking. This paper aims to review the state of the art in these two key elements.

The key elements involved in localization and mapping of AUVs lie in two aspects, namely hardware and software. In this paper, hardware means sensors while software represents algorithms utilized in AUV navigation. To a large extent, the sensors' accuracy and the selection of data processing algorithms determine the overall accuracy of AUV navigation. When an AUV has only GPS/INS sensors on-board, the accuracy of its position estimation and environment mapping will depend on the accuracy of both GPS and INS sensors, as well as the sensor fusion algorithms that are adopted, typically Kalman filters rather than triangulation. Therefore, gaining sufficient knowledge of sensors is the prerequisite of developing the localization and mapping systems for AUVs. This is also the reason for Section 2 to summarize sensors accuracy for underwater localization and mapping.

During last decades, various algorithms have been proposed to solve underwater localization and mapping problems according to specific sensors used. Grasping a comprehensive picture of what and how algorithms are applied for underwater localization and mapping will be quite instructional for algorithm development in the application of AUVs. As can be seen in this paper, especially in Section 3 and 4, most of localization algorithms are based on triangulation and Kalman filter when Underwater Acoustic Positioning System (UAPS) are used. Recently, various sensor fusion algorithms have been developed to integrate several sensors such as GPS, INS and DVL. Once localization is conducted, mapping is realized by utilizing sonar sensors such as multi-beam sonar and side-scan sonar. After the year 2000, SLAM algorithms have been developed for autonomous robots, which in turn have been applied in AUVs (Ribas et al., 2006), (Leonard and Feder, 2001) and (Tena Ruiz et al., 2004).

Up to now, several review papers on the navigation of AUVs have been presented. (Leonard et al., 1998) surveyed the navigation methods for AUVs and categorised them into three groups: (1) dead-reckoning and inertial navigation systems; (2) acoustic navigation; (3) geophysical navigation techniques. However, the review discussed the general SLAM instead of underwater SLAM since no SLAM algorithm had been used in AUVs at that time. (Kinsey et al., 2006) surveyed advances in AUV navigation in the aspects of sensor technology, underwater navigation methodologies and future challenges. The structure in (Kinsey et al., 2006) is similar to ours, but with less comprehensive statistical analysis of sensors and algorithms used in underwater navigation. This paper intends to provide a comprehensive review on various sensors and algorithms used in AUVs according to their application situation, pros and cons, as well as statistical analysis.

The rest of the paper is organized as follows. Section 2 overviews different types of sensors used for underwater localization and mapping in terms of basic working principle, characters, their advantages and disadvantages. Section 3 summarizes various algorithms used for underwater localization and mapping according to their application situations, advantages and limitations, etc. By studying the major AUV application platforms published in literature, Section 4 provides the statistic graph of the AUV platforms according to the usage of different sensors and the utilization of various algorithms. Section 5 draws the conclusion from what has been discussed in the paper and makes suggestions for future research.

2. Sensors Used for Underwater Localization and Mapping

To deal with dynamical changes in the real world, various sensors are deployed on UAVs for navigation and goal seeking. Since sensor characters determine the system architecture and navigation algorithms, it is necessary to understand the characteristics of various sensors used for localization and mapping prior to system design and development. The popular sensors include, but not limited to, GPS (Global Positioning System), INS (Inertial Navigation System), Doppler Velocity Log (DVL), Mechanically Scanning Imaging Sonar (MSIS), sonar, visual sensor, and Underwater Acoustic Positioning System (UAPS), etc. This section will outline these sensors briefly.

2.1 GPS/INS

GPS (Global Positioning System) is a space-based global navigation satellite system (GNSS) that provides location and time information in all weather, anywhere on or near the Earth (Wikipedia, 2012a). A small GPS receiver module is able to gain location and time information with accuracy being 1-10 meters. However, GPS suffers from various errors including numerical errors, atmospherics effects, ephemeris errors, multipath errors and other effects (Grewal et al., 2007).

INS (Inertial Navigation System) is a dead reckoning navigation system that consists of a computer, motion sensors (accelerometers) and rotation sensors (gyroscopes) to continuously calculate the position, orientation, and velocity (direction and speed of movement) of a moving object without the need for external references (Wikipedia, 2012b). The main advantages of inertial navigation over other forms of navigation include (Grewal et al., 2007): (i) It is autonomous and does not rely on any external aids or on visibility conditions. It can operate in tunnels or underwater as well as anywhere else. (ii) It is inherently well suited for integrated navigation, guidance, and control of the host vehicle. (iii) It is immune to jamming and inherently stealthy. It neither receives nor emits detectable radiation and requires no external antenna that might be detectable by radar.

GPS is capable of improving its accuracy if it is integrated with an INS to compensate for intermittent reception caused by either wave action or deliberate submergence. Therefore, integrated GPS/INS systems have been applied to aircraft and space shuttle guidance and navigation (Barnes et al., 1996, Braden et al., 1990, Gray and Maybeck, 1995), balloon navigation (Jekeli, 1992), missile systems (Ornedo et al., 1998), land vehicles (Martin and Vause, 1998), and mobile robots (Barshan and Durrant-Whyte, 1995, Sukkarieh et al., 1998). In these applications, GPS data are continuously available in short intervals, and INS data are used to navigate between GPS fixes. Similar to these applications, integrated GPS/INS system can also be applied to AUVs working in shallow sea without a long period of submergence. When AUVs are surfaced, they take advantage of GPS to localise themselves accurately, while they are in underwater, INS replace GPS to localise though with relatively low accuracy compared to the circumstance on the surface (Yun et al., 1999).

Although GPS/INS integrated system can achieve relatively high accuracy of localization, it is limited to shallow water environment with short period of working time. Since INS has accumulated errors, its localization error will continue to increase if it is not corrected by GPS for a long time.

2.2 DVL

DVL has three or four downward looking beam transducers that are typically mounted at about 30° to the instrument's vertical axis. The Doppler sensor measures the apparent bottom velocity along each of three or four beams and processes the four responses to compute a vector of velocities in the instrument frame according to the Doppler Effect (Rigby et al., 2006). The velocity vector in the instrument frame is then rotated to the world frame by multiplying it with a rotation matrix composed of roll, pitch and yaw angles with respect to the world frame. The velocities can then be integrated to compute bottom track position. However, the integration process makes the calculated position error unbounded, which results in the fact that DVL is rarely used alone for underwater navigation. Therefore, DVL is often fused or combined with other sensors such as INS (Hui and Fengle, 2002, Zhao and Gao, 2004) and UAPS (Rigby et al., 2006).

2.3 MSIS

MSISs perform scans in a 2D plane by rotating a fan-shaped sonar beam through a series of small-angle steps (Ribas et al., 2008). For each emitted beam, an echo intensity profile is returned from the environment. Gathering all this information within a complete 360° produces an acoustic image of the surrounding environment. The beam usually has both vertical and horizontal beam widths, and the vertical beam width is larger than horizontal one. It takes several seconds for MSIS to complete one 360° scanning rotation, during which the MSIS motion will distort the image. Therefore, it is necessary to correct the distorted image by the vehicle motion. When MSIS is used for localization and mapping in AUVs, it is often used for providing the filtering algorithm with the observation part, either represented in the form of *feature* extracted from the image (Ribas et al., 2008) or in the form of template used in scan matching (Hernández et al., 2009).

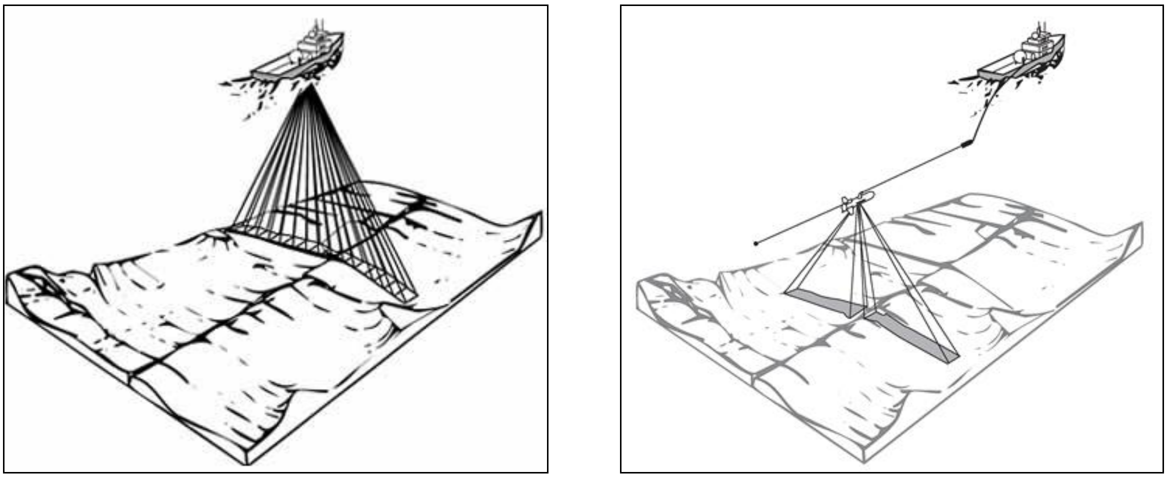
2.4 Side-scan Sonar and Multi-beam Sonar

Sonar (SOund Navigation And Ranging) sensors use sound propagation to achieve navigation, object detection and communication. Sonar works better in underwater than on land since sound transmits faster in water than in the air. Thus, Sonar is the most widely used range sensor for underwater vehicles. There are two types of frequently used sonars for underwater localization and mapping, namely multi-beam sonar and side-scan sonar. They share some common characters, though with some differences.

As shown in (a**) Multi-beam Sonar** **(b) Side-scan Sonar**
Figure 1 (a), a multi-beam sonar is an instrument that can map more than one location on the ocean floor with a single ping and with higher resolution than those of conventional single-beam sounders (Instruments, 2000). Unlike the single-beam echo sounder which can only trigger one beam of sound for one ping, a multi-beam sonar can perform the job of single-beam at several different angles for one ping, which significantly makes the scanning much faster and more accurate than a single beam sounder. Generally, multi-beam sonar is installed on the hull of a vessel looking down toward the seafloor and used for mapping, which produces a high accuracy of location information of the vessel. Also, some researchers employ forward-looking multi-beam sonar for obstacle avoidance or localization (Petillot et al., 2001).

Side-scan sonar (see (a**) Multi-beam Sonar** **(b) Side-scan Sonar**
Figure 1(b)) is similar to that of multi-beam sonar, but is dragged by the ship to near the ocean floor instead of being installed on the hull of the ship. This is due to the fact that the sonar device obtains a higher resolution when it is close to the sea floor (Survey, 2010). It is is used to create images of the sea floor and debris that lies on it. Side-scan sonar can be used in marine or underwater fields for various purposes (Tena Ruiz et al., 2004). The collected image data from side-scan sonar is processed by some algorithms so that extracted features could match with a priori map for AUV to localise.

Although multi beam and side-scan sonar are not simultaneously installed on the same AUV in most cases, some researchers such as (De Moustier and Matsumoto, 1993) combined these two sonars and believed that a combination of them could be a very effective tool to quantify sea bottom types on a regional basis and develop automatic seafloor classification routines for mapping.



(a) Multi-beam Sonar (b) Side-scan Sonar

Figure 1: Working sonars (Oceanic Imaging Consultants, 2012).

2.5 Visual sensor

Video camera and laser-based vision system are the two main visual based sensors used for localization and mapping in an underwater environment because of their low cost and rich information. Although video camera is limited to short range due to low visibility and lighting factors in underwater circumstances, it is widely applied by researchers conducting underwater localization and mapping experiment and practise (Carreras et al., 2003, Salvi et al., 2008, Zhang et al., 2004).

A laser-based vision system is usually composed of a laser projector and a camera, which cooperate with each other to recognise the 3D feature of objects. Compared to a single camera, it is not subject to the low visibility and bad lighting condition of underwater environments, as the laser projectors can emit very powerful laser beam which can hardly be weakened by water. Therefore, a laser-based vision system can realise more accurate localization than a single camera (Karras et al., 2006).

2.6 Underwater Acoustic Positioning System

Underwater Acoustic Positioning Systems (UAPS) measure positions relative to a framework of baseline stations, which must be deployed prior to operations. The location of baseline transponders either relative to each other or in global coordinates must then be measured precisely using triangulation. UAPS are generally categorised into four broad types: Long Baseline (LBL) Systems, Short Baseline (SBL) Systems, Ultra Short Baseline (USBL) Systems and GPS Intelligent Buoys (GIB). The former three baseline systems are defined by the distance between acoustic baselines, i.e. the distance between the active sensing elements.

2.6.1 LBL Systems

The baseline length of LBL systems is from 100 to 6000+ meters. LBL systems use a sea-floor baseline transponder network and derive the position with respect to the network. The transponders are typically mounted in the corners of the operations site. The position is generated from using 3 or more time of flight ranges to/from the seafloor stations using triangulation. LBL systems yield very high accuracy of generally better than 1 m and sometimes as good as 0.01m along with very robust positions (Foley and Mindell, 2002). One of the typical applications of LBL for localization and navigation of AUVs can be seen in (Matos et al., 1999), where a LBL based navigation system was successfully developed for an AUV.

2.6.2 SBL Systems

The baseline length of SBL systems is from 20 to 50 meters. SBL systems operate on a similar principle as LBL, but the receiving hydrophones are usually mounted at fixed locations on the vessel floating on the water surface. Then AUVs obtain their position by measuring the time of arrivals (TOA) between a transponder attached on the AUV and the hydrophones on the vessel. Since the vessel is subject to pitch, roll and yaw movements due to water current, the calculated position of the underwater object has to be corrected using a vertical reference unit (VRU) and a heading reference unit (HRU) (Vickery, 1998). In a contrast to the widely used application of USBL in underwater navigation, quite few SBL systems were applied to this field.

2.6.3 USBL Systems

The baseline length of USBL systems is less than 10cm. USBL is also known as Super Short Baseline (SSBL). Unlike LBL and SBL systems, which calculate positions by measuring multiple distances and then applying triangulation, the USBL transducer array is used to measure the target distance from the transducer pole by using signal run time, and the target direction by measuring the phase shift of the reply signal as seen by the individual elements of the transducer array. The combination of distance and direction fixes the position of the tracked target relative to the surface vessel(Surveyor et al., 2013). Like SBL systems, the calculated position of the AUV has to be corrected using VRU and HRU. Therefore, USBL is generally integrated with other dead reckoning sensors such as DVL and INS for the accurate localization and navigation of AUV, by adopting filtering algorithms such as Kalman filter, Extended Kalman filter and Particle Filter etc.(LI et al., 2008, Morgado et al., 2006, Rigby et al., 2006)

2.6.4 GIB systems

The GIB system consists of four surface buoys equipped with DGPS receivers and submerged hydrophones. Each of the hydrophones receives the acoustic impulses emitted periodically by a synchronized pinger installed on-board the underwater platform and records their TOA (Alcocer et al., 2006). The TOA is then converted to distances by multiplying it with the underwater speed of sound. The position of the underwater platform can be calculated either by triangulation or EKF-based triangulation (Alcocer et al., 2007).

In order to summarize the characters of aforementioned sensors, Table 1 is made to show the characteristics of various sensors used for underwater localization and mapping. Based on this table, it is easy to draw a conclusion about the major advantages and disadvantages of these sensors which can be seen in Table 2.

Sensors	Data format	Cost	Weight	Accuracy	Deployment Difficulty	Working Depth	Power Consumption
GPS/INS	Satellite time; Inertial information	Low	Light	Low	Easy	Shallow	Low
DVL	Velocity	High	Light-Heavy	Medium	Medium	Deep	High
MSIS	Sonar image	Medium	Light	Medium	Medium	Medium	Medium
Side-scan Sonar	Sonar image	Medium	Heavy	Medium	Medium	Deep	Medium
Multi-beam Sonar	Sonar image	Medium	Light	Medium	Medium	Deep	Medium
Camera	Visual image	Low	Light	Low	Easy	Shallow	Low
Laser-based Vision System	Range and Visual image	High	Medium	High	Medium	Deep	Medium
LBL systems	Range	High	Heavy	High	Difficult	Deep	High
USBL systems	Range and Angle	High	Heavy	High	Medium	Medium	Medium
SBL systems	Range	High	Heavy	High	Medium	Medium	Medium
GIB	Satellite time, Range	High	Heavy	High	Medium	Medium	Medium

Table 1: Character of various sensors used for underwater localization and mapping

Table 2: Advantages and disadvantages of various sensors

Sensors	Advantages	Disadvantages
GPS/INS	Low cost, light, easy to deploy, require no external aid (INS).	Only suitable for shallow environment, low accuracy.
DVL	Directly provide velocity, requires no external aid.	Too heavy for small AUVs, high cost and high power consumption.
MSIS	Relatively low cost, light weight suitable for small AUVs.	Suffer from distortion caused by vehicle motion.
Side-scan Sonar	Provide rich information about the environment, accurate mapping.	Too heavy for small AUVs, high cost.
Multi-beam Sonar	Provide complete swath coverage of the surveyed area.	Beam limited in the near-nadir region.
Camera	Low cost, rich information about the environment, easy to deploy.	Subject to low visibility and bad lighting condition, only suitable for shallow environment.
Laser-based Vision System	Not subject to the low visibility and bad lighting condition. High accuracy.	High cost.
LBL systems	High position accuracy independent of water depth over large areas.	Complex, expensive, difficult to deploy, require comprehensive calibration at each deployment.
USBL systems	No need to deploy transponders on the seafloor, low system complexity.	Detailed system calibration required, absolute position accuracy depends on additional sensors-gyro and VRU.
SBL systems	No need to deploy transponders on the seafloor.	Detailed offshore calibration of system required, absolute position accuracy depends on additional sensors-gyro and VRU.
GIB	No need to deploy transponders on the seafloor, able to obtain global location, calibration-free with accuracy similar to LBL systems.	Pre-deployment is required.

3. Algorithms used for Underwater Localization and Mapping

After sensor data has been obtained from sensors described above, algorithms should be designed and executed to calculate and present the location and mapping information which will be used for navigation of AUVs. Since different sensors have their own characteristics, the formulations of their corresponding algorithms vary. This section will summarize the various algorithms used for AUVs over the past, and analyse the advantages and disadvantages of each type of them. These algorithms can be classified into: trilateration and triangulation, sensor fusion, scan matching and SLAM.

3.1 Trilateration and Triangulation

Lateration is the simplest algorithm used for determining the position of an AUV, given several distances from the vehicle to other beacons whose location is known in advance. The AUV position can be calculated by solving a non-linear optimization problem whose objective function is the minimization of the error between the actual ranges and the expected ranges from the vehicle to the beacons. For a 2D localization problem, the minimum number of known beacons for lateration is 3, which produces the name of the localization approach - trilateration. For a 3D localization problem, the minimum number is 4. When angles between beacons are involved, the approach is called Triangulation. Several triangulation algorithms have been proposed, such as *Geometric Triangulation*, *Iterative Search*, *Newton-Raphson Iterative Search* and *Geometric Circle Intersection* (Cohen and Koss, 1993), *triangulation using three circle intersection* (Fuentes et al., 1995), and *Generalized Geometric Triangulation Algorithm* (Esteves et al., 2003). Lateration and angulation work quite well as long as the ranges and angles are properly and stably given by range sensors. This is also the reason for why they are widely used in UAPS since all types of UAPS has pre-deployed beacons with known either absolute or relative positions. However, there are at least two common restrictions to these algorithms: 1) areas of the plane with less than three (for 2D and four for 3D) visible beacons are unsuitable for robot localization; 2) the algorithms will fail to calculate the robot position if the vehicle and the beacons all lie in the same circumference. In particular, for 3D localization, the four beacons should not be in the same plane, otherwise it is impossible to obtain 3D position of the vehicle.

3.2 Sensor Fusion

Generally speaking, fusing data from multiple sensors is able to provide more accurate and robust localization and mapping results than using only individual sensors separately. Throughout the literature, the most widely applied algorithms for sensor fusion are Kalman Filter (Welch and Bishop, 1995) and their variants, due to their easiness, real-time ability and robustness to implement. For underwater navigation, sensor fusion is always related to INS which is typically considered as the core sensor fused with other sensors such as GPS, DVL and both GPS and DVL. Therefore, a brief review of various Kalman filtering based algorithms used for underwater navigation is presented as follows by taking INS/GPS, INS/DVL and INS/GPS/DVL as examples:

3.2.1 Kalman Filter

A Kalman Filter estimates the state of a dynamic system with two different models namely kinematic and observation models. The kinematic models describe the state transition of the system, while observation models represent the relationship between the environment and the state of the system. By iteratively calculating the Kalman equations regarding the kinematic model and the observation model, it provides optimal estimation of the system state. Kalman filter solves problem where both the system process and observation model are *linear*. However, almost all the dynamic process in the real world is *non-linear*, therefore, instead of being used directly in practice, Kalman filter is often considered as the basic theoretic framework for its variants that are more practically utilized.

3.2.2 Extended Kalman Filter

Extended Kalman Filter (EKF) is the most successful variant of Kalman Filter as it is able to achieve good accuracy of state estimation in most of practical circumstances where system dynamic and observation models are non-linear. EKF performs calculation of Kalman Filter by linearizing the estimation around the current estimate using the first order of partial derivatives (also known as Jacobians) of the process and measurement functions (Welch and Bishop, 1995). Like its popular use in other applications of state estimation, EKF has been vastly employed for sensor fusion in underwater navigation. For example, (Faruqi and Turner, 2000) utilized EKF technique for the integration of GPS and INS. In their system, the errors of position, velocity, attitude, accelerometer bias, gyro drifts, GPS clock time and frequency bias are the system states that should be estimated; the typical INS equations including integral of acceleration and gyro rate compose the dynamic model and raw pseudo range and pseud-range-rate data from GPS are utilized as measurements to the filter. EKF has also been utilized for the integration of INS/DVL (Hui and Fengle, 2002) and the fusion of INS/GPS/DVL (Zhao and Gao, 2004).

It should be noticed that there is a fundamental disadvantage of EKF, that is, due to the linearization in dynamic and observation models, the filter may quickly diverge if the initial estimate of the states is wrong or if the models are not accurately built. Furthermore, the higher the nonlinearities are, the larger the estimation errors will be (Thrun et al., 2005).

3.2.3 Unscented Kalman Filter

Instead of only taking first order approximation of Taylor series expansion like EKF, Unscented Kalman Filter (UKF) uses a deterministic sampling approach to capture the mean and covariance estimates with a minimal set of sample points namely *sigma points*. In the general case, these *sigma points* are located at the mean and symmetrically along the main axis of the covariance. It has the 3rd order (Taylor series expansion) accuracy for Gaussian error distribution of any non-linear system (Wan and Van Der Merwe, 2000). UKF is claimed to have obvious advantage over EKF in terms of estimation accuracy although EKF is slightly faster than UKF in practice. Another advantage of UKF over EKF is that it does not require the computation of Jacobians, which are difficult in some circumstances (Thrun et al., 2005). (Bao and Zhou, 2008, Shen et al., 2007, Shin, 2001, Zhang et al., 2005) adopted UKF in the algorithms integrating GPS and INS.

3.2.4 Adaptive Kalman Filter

It is known that the optimality of estimation algorithm in basic KF, EKF and UKF is closely related to the accuracy of *a priori* knowledge about the process and measurement noise (Mehra, 1970). However, in these 3 algorithms, it is assumed that the process covariance matrix (Q) and the measurement noise covariance (R) are known *a priori* and remain unchanged during the continuous iteration. But in most practical applications, this assumption is not true, which will result in estimation divergence when the actual covariance matrix is far away from the unchanged one. Therefore, it is necessary for Q and R to be adaptively determined.

Generally, there are two approaches that have been proposed for adaptive Kalman filer: multiple model adaptive estimation (MMAE) and innovation adaptive estimation (IAE)(Mohamed and Schwarz, 1999). Both utilize the information in the innovation sequence but with different implementation. The innovation is represented by the difference between the actual measurement and its predicted value. In the MMAE approach (Magill, 1965, White et al., 1998), a bank of Kalman filters runs in parallel with different models for the statistical filter information matrices Q and R. Each filter of the bank have its own estimate, with a weight that is calculated based on the innovation. Then the adaptive optimal state estimate can be obtained as the weighted sum of the estimates produced by each of the individual Kalman filters.

For the IAE approach, the covariance matrices R and Q are adapted as the measurements evolve with time by taking the innovation sequence into account. According to the specific formats of using the innovation sequence, IAE can be categorized into three types which are moving estimation window based IAE (Mehra, 1970, Mehra, 1971), Maximum Likelihood based IAE (Mohamed and Schwarz, 1999) and Fuzzy Logic based IAE (Loebis et al., 2004, Sasiadek and Wang, 1999, Sasiadek et al., 2000). Due to its simplicity and effectiveness, Fuzzy logic based IAE have been widely adopted in the researches on INS/GPS integration, such as (Xu et al., 2005, Zhang et al., 2008, Zhang and Wei, 2003) etc..

3.3 Scan Matching

Scan matching aims to find the translation and rotation of a scan contour in such a way that a maximum overlap occurs with either a known map (i.e., position estimation) or a previous scan (i.e., motion estimation) (Martínez et al., 2006). According to (Martínez et al., 2006), the methods of scan matching can be classified into three categories: feature-based techniques, compact data methods and point matching techniques. Figure 2 chronologically gives the specific classification of the scan matching algorithms and their related references. Among all the scan matching methods, the Iterative Closest Point (ICP) algorithm is the most popular one (Besl and McKay, 1992) because of its simplicity and effectiveness. Based on the basic ICP algorithm, several its variants were subsequently proposed to improve the performance in terms of time effeciency and accuracy, such as IDC (Lu and Milios, 1997), NDT (Biber and Straßer, 2003), MbICP (Minguez et al., 2005), pIC (Montesano et al., 2005) and PSM (Burguera et al., 2007).

While most of the scan matching algorithms focus on motion estimation for terrestial robots either with laser range readings or sonar range readings, few of them are related to AUV navigation except MSISpIC (Hernández et al., 2009) and (Burguera et al., 2010). As an extension of the pIC (Montesano et al., 2005) algorithm, MSISpIC proposed a scan grabbing algorithm using range scans gathered with a MSIS to combine with pIC for localization of the AUV. Although the experiments show satisfactory results, the environment is not long engouth to give more convincing effects. In addition, the experiment could not improve the efficiency of MSISpIC in a cluttered environment since the environment used for experiments is semi-artificial.

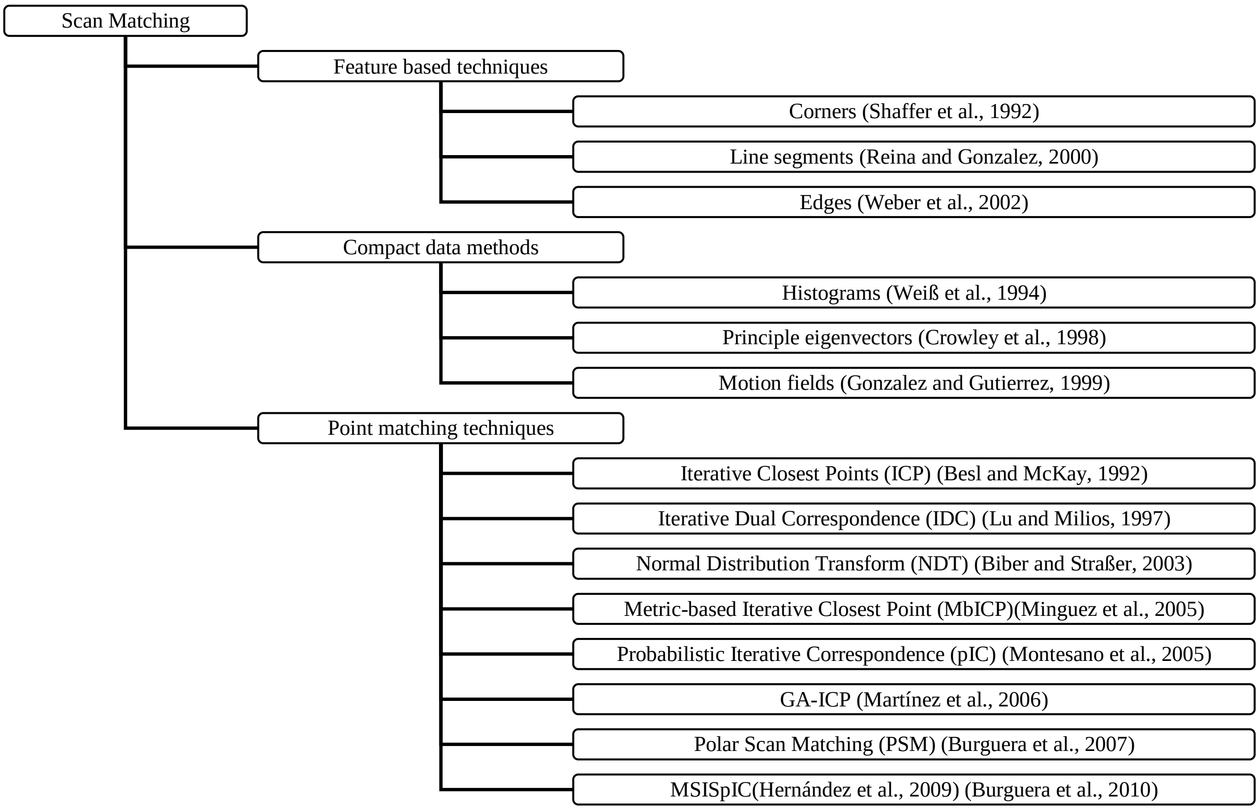


Figure 2: Classification of scan matching algorithms and related references

3.4 SLAM

It can be noticed that all the aforementioned algorithms mainly focus on localization problems without taking mapping problems into account. However, the autonomy of AUVs typically demands a map of the environment for path planning. Therefore, finding a solution to the mapping problem is also necessary for autonomous navigation of AUVs. It is normal that localization and mapping problem can be solved independently. However, the simultaneous localization and mapping (SLAM) algorithm enables a AUV to be placed at an unknown location in an unknown environment so that it incrementally builds a consistent map of the environment while simultaneously determining its location within this map (Durrant-Whyte and Bailey, 2006).

Throughout last two decades, various SLAM algorithms have been proposed and applied successfully to solve the SLAM problem. Table 3 summaries the most popular SLAM algorithms widely used in the literature, in the aspects of their related references which firstly proposed the corresponding algorithm, the optimizer the algorithm utilizes, the map representation method that the algorithm is suitable for and the advantages and disadvantages of the algorithm.

Table 3: Summary of major SLAM algorithms

Algorithm	Optimizer	Map representation	Advantages	Disadvantages
EKF-SLAM(Leonard and Durrant-Whyte, 1991, Moutarlier and Chatila, 1989)	EKF	Feature-based map	Earliest and most influential, applies to online implementation.	Linearize only once, quadratic update time, feature number limitation, need for sufficiently distinct landmarks.
Fast-SLAM 1.0(Montemerlo et al., 2002)	Rao-Blackwellized Particle Filer	Feature-based map and Grid Based map	Implementation time logarithmic in the number of features, cope with non-linear motion models, full and online SLAM, simple, fast and easy to implement.	Slower convergence speed than EKF-SLAM, lack of long-range correlations, generating samples inefficiently.

Algorithm	Optimizer	Map representation	Advantages	Disadvantages
Fast-SLAM 2.0 (Montemerlo et al., 2003)	Rao-Blackwellized Particle	Feature-based map and Grid Based map	More efficient than Fast-slam 1.0, needs fewer particles than Fast-SLAM 1.0.	More difficult to implement than Fast-slam 1.0.
Sparse Extended Information Filter SLAM(Thrun et al., 2004)	Sparse Extended Information Filter	Feature-based map	Online and efficient, update loop is constant time.	Linearize only once, Less accurate than EKF or Graph-SLAM.
UKF-SLAM(Andrade-Cetto et al., 2005)	Unscented Kalman Filter	Feature-based map	Better accuracy of linearization of non-linear model than EKF-SLAM Not require computation of Jacobians.	Slightly slower than EKF-SLAM.
Graph-SLAM(Thrun and Montemerlo, 2006)	Any least squares technique	Feature-based map and topological map	Solves full SLAM, able to acquire much larger maps than EKF-SLAM, linearize more than once, revise past data association, more accurate map than EKF.	Offline SLAM, require inference when calculating data association probability.

Underwater SLAM has many more challenging issues compared to land SLAM, due to the unstructured nature of the underwater scenarios and the difficulty to identify reliable features. Many underwater features are scale dependant, sensitive to viewing angle and scale. Therefore, fewer research works have been conducted on applying SLAM algorithms for underwater navigation of AUVs until now. In underwater SLAM implementations, imaging sonar (Ribas et al., 2006) is widely used, the most common filtering technique is the EKF (Mahon and Williams, 2004, Ribas et al., 2008) and point features (He et al., 2009, Leonard and Feder, 2001, Williams and Mahon, 2004) are commonly used to represent the map. Some approaches use side-scan sonar (Tena Ruiz et al., 2004) or optical cameras (Aulinas et al., 2011, Salvi et al., 2008). The use of EKF based SLAM is able to handle uncertainties properly; however, the computational cost associated with EKF grows with the size of the map. In addition, linearization errors accumulate in long missions, increasing the chance of producing inconsistent mapping solutions.

4. Statistics of AUV platforms

In order to grasp the whole picture of AUV applications in terms of the usage of sensors and utilization of algorithms, the statistical analysis on different AUV platforms is presented in this section. In total, 35 AUV application platforms are studied. Table 4 lists their references, affiliations, platform name, core sensors, the localization and mapping algorithms in the chronological order.

Figure 3 shows the ratio of sensors used in 35 AUV application projects, which largely indicates the percentage of the specific sensor used on AUV platforms. It can be clearly seen that INS and DVL are the first and second most frequently used sensors. The reason for this phenomenon may be attributed to the fact that INS and DVL are the most suitable sensors to provide the dead reckoning information for underwater vehicles due to their self-contained characteristics. The dead reckoning information from INS and DVL can then either be fused with other sensors by application sensor fusion algorithms or be used for the prediction part in the SLAM framework. It should be also noticed that the percentage of LBL, USBL and MSIS demonstrates that they play important roles in the localization for some AUVs.

Unlike the sensors whose types are almost fixed within several kinds, the types of algorithms used for locolization and mapping of AUVs are more diverse than that of sensors. Figure 4 gives the ratio of algorithms used in 35 AUV application projects. Not surprisingly, due to its simpleness and real-time features, EKF are the most popular algorithm used for both sensor fusion and filtering. Triangulation is also used frequently since many AUV platforms take advantage of acoustic navigation systems such as USBL, LBL and SBL most of which utilize triangulation to calculate the location of AUVs. As the most typical algorithm, EKF-SLAM has the use percentage more than other SLAM algorithms such as FastSLAM

(Woock and Frey, 2010), ESEIF SLAM (Walter et al., 2008), constant time SLAM (Newman et al., 2005) and MHTF SLAM (Tena Ruiz et al., 2001).

It can also be concluded that most of localization algorithms are triangulation and Kalman filter (when UAPS are used), including EKF based sensor fusions to integrate several sensors such as GPS, INS and DVL before 2000s. When localization is completed, mapping is then realized by utilizing sonar sensors such as multi-beam sonar and side-scan sonar. After the year 2000, SLAM algorithms have been successfully applied in AUVs , exemplified by (Ribas et al., 2006), (Leonard and Feder, 2001) and (Tena Ruiz et al., 2004).

Table 4: Applications of AUV platforms

Reference	Affiliation	Platform	Core sensors	Localization and mapping Algorithms
(Butler and den Hertog, 1993)	ISE Research (Canada)	Theseus	INS/DVL	Sensor Fusion (EKF)
(Egeskov et al., 1994)	Technical University of Denmark (Denmark)	MARIUS AUV	INS, LBL, Depth Cell, Echo sounder	Triangulation and EKF
(Bellingham et al., 1994)	MIT Sea Grant College Program (USA)	Odyssey II	INS, LBL, USBL, Side Scan Sonar	Triangulation and EKF
(An et al., 1997)	Florida Atlantic University (USA)	OEX AUV	DGPS/INS, Doppler sonar	Sensor Fusion (Heuristic Fuzzy filtering)
(Opderbecke, 1997)	French Research Institute for Exploitation of the Sea (France)	Nautile, Cyana AUV	USBL	EKF
(Yuh et al., 1998)	University of Hawaii (USA)	SAUVIM AUV	DGPS, DVL, Depth Sensor, INS.	Sensor Fusion (EKF)
(Larsen, 2000)	Marindan A/S (Denmark)	MARIDAN A UV	Synthetic LBL,DVL, INS,GPS	Sensor Fusion (EKF)
(Yoerger et al., 2000)	Woods Hole Oceanographic Institution (USA)	ABE AUV	LBL	Triangulation and KF
(Austin et al., 2000)	Woods Hole Oceanographic Institution (USA)	REMUS AUV	LBL	Triangulation
(Newman and Durrant-Whyte, 1998, Williams and Mahon, 2004, Williams et al., 2000)	University of Sydney (Australia)	Oberon	IMU, Imaging Sonar, Camera	EKF-SLAM
(Tena Ruiz et al., 2001)	Heriot-Watt University (UK)	RAUVER	Multi-beam sonar	Multiple Hypothesis Tracking Filter (MHTF) based SLAM
(Yun et al., 2001)	Naval Postgraduate School (USA)	SANS AUV	INS/GPS	Sensor Fusion (EKF)
(Sherman et al., 2001)	Scripps Institution of Oceanography (USA)	Spay Glider	GPS	GPS related algorithm
(Baccou and Jouvencel, 2002)	University of Montpellier (France)	Taipan AUV	Single beam Sonar	Kalman Filter
(Blain et al., 2003)	Hydro-Québec's research institute (Canada)	Hydro-Québec ROV	Fibre gyro, DVL, accelerometers, GPS	Sensor Fusion (EKF)
(Jalving et al., 2003)	Norwegian Defence Research Establishment (Norway)	HUGIN AUV	DVL, INS, GPS	Sensor Fusion (EKF)
(Jalbert et al., 2003)	Autonomous Undersea Systems Institute (USA)	SAUV II	GPS, compass, Altitude sensor, depth sensor, speed sensor.	GPS related algorithm
(Asada et al., 2004)	University of Tokyo (Japan)	r2D4 AUV	INS, Side-scan Sonars	Inertial Navigation equations

Reference	Affiliation	Platform	Core sensors	Localization and mapping Algorithms
(Loebis et al., 2004)	University of Plymouth and Cranfield University (UK)	Hammerhead AUV	GPS and INS	Adaptive Kalman Filter
(Zhao and Gao, 2004)	Harbin Engineering University (China)	Any AUVs	GPS/INS/DVL	EKF
(Newman et al., 2005)	Oxford University (UK)	Odyssey III	DVL/INS, 16 element Synthetic Aperture Sonar	Constant Time SLAM
(Spiewak et al., 2006)	Lirmm Montpellier (France)	H160	GPS, DVL	Sensor Fusion (EKF)
(Schofield et al., 2007)	Rutgers University (USA)	Slocum glider	GPS, attitude sensor, depth sensor, and altimeter	GPS related algorithm
(Yeo, 2007)	Hafmynd company (Iceland)	Gavia AUV	INS/DVL, GPS, LBL	Sensor Fusion (EKF)
(Walter et al., 2008)	Massachusetts Institute of Technology (USA)	HAUV AUV	DVL, DIDSON imaging sonar	Exactly Sparse Extended Information Filter (ESEIF) SLAM
(Ribas et al., 2008)	Universitat de Girona (Spain)	Ictineu AUV	DVL, Compass, MSIS, INS	EKF SLAM
(Armstrong et al., 2009)	University of Idaho (Russia)	AUV	IMU, acoustic range, ransponders	EKF
(Hernández et al., 2009)	Universitat de Girona (Spain)	Ictineu AUV	DVL, Compass, MSIS, INS	Scan Matching (Probabilistic Iterative Correspondence)
(Mallios et al., 2010)	Universitat de Girona (Spain)	Ictineu AUV	DVL, Compass, MSIS, INS	Scan Matching and EKF SLAM.
(Morgado et al., 2010)	the Institute for Systems and Robotics, Lisbon (Portugal)	Any AUVs	USBL/INS	Sensor Fusion (EKF)
(Woock and Frey, 2010)	Fraunhofer Institute of Optronics, System Technologies and Image Exploitation IOSB (Germany)	TIETeK AUV	DVL, IMU and Side-Scan Sonar	FastSLAM and EKF SLAM
(Augenstein and Rock, 2011)	Stanford University (USA)	ROV Ventana	Monocular vision	FastSLAM
(Liu et al., 2011)	Northwestern Polytechnical University (China)	Any AUVs	INS/DVL	Sensor Fusion (UKF)

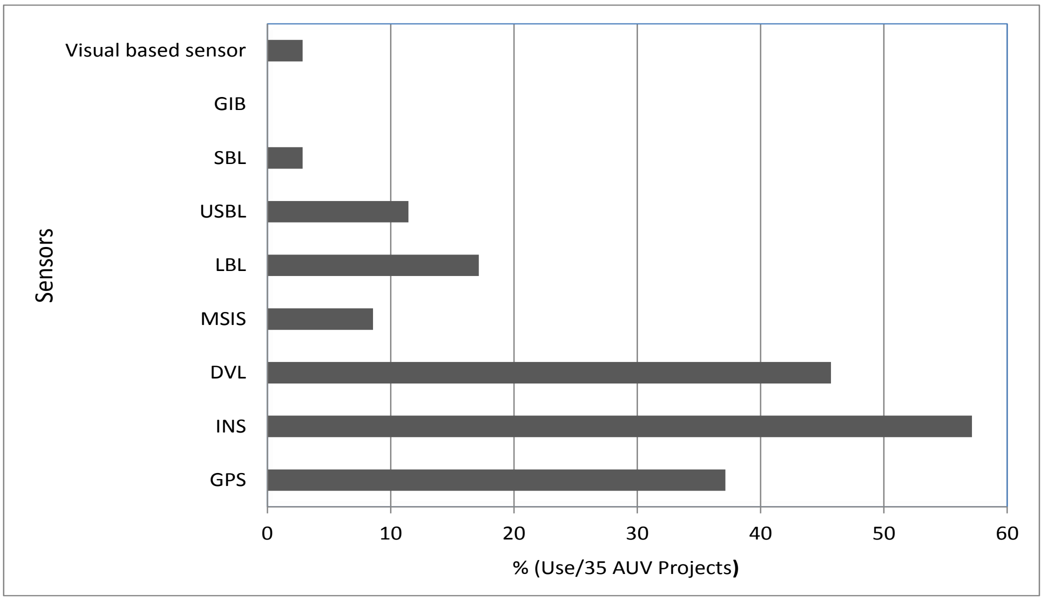


Figure 3: Ratio of sensors used in 35 AUV application projects

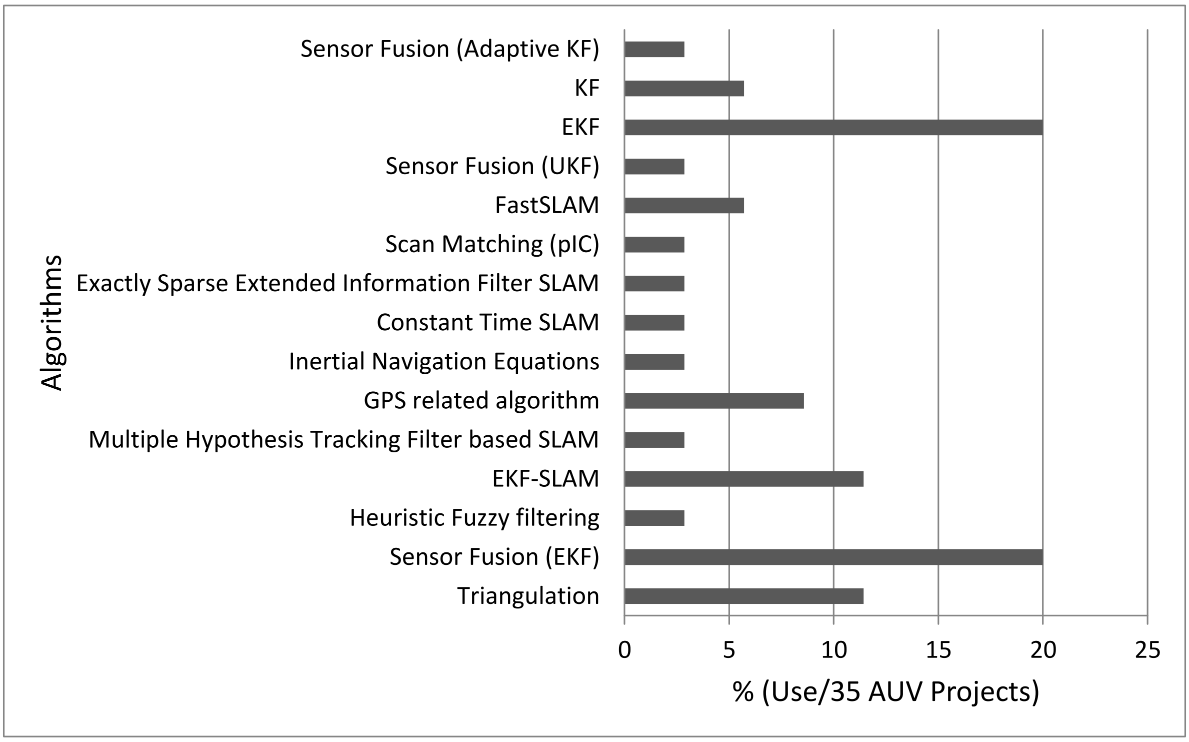


Figure 4: Ratio of algorithms used in 35 AUV application projects

5. Conclusion

Localization and mapping are considered as the most fundamental two aspects of AUVs navigation. This paper outlines the two key elements in underwater localization and mapping for AUVs, namely sensors and algorithms. Various sensors used for AUVs have been reviewed in terms of basic working principle, characters, the advantages and disadvantages of these sensors. Then, a variety of algorithms used for underwater localization and mapping are explained according to their application situations, advantages and limitations, etc. Additionally, 35 AUV platforms are statistically analysed based on the application circumstances of sensors and algorithms that are practically used.

Although a great deal of research work has been conducted to realize autonomous localization and navigation for AUVs, various challenging issues remains to be addressed, including (i) The dynamic and unstructured characteristics of underwater environments require sensors with a high resolution and accuracy. This is very challenge. (ii) If the environmental feature is not intuitive, it is necessary to apply proactive SLAM to explore useful information by deploying artificial landmarks. (iii) Since high accurate sensor systems such as LBL, USBL and SBL have a large size and high cost, it is impractical to use these sensor systems for localization of small bio-inspired vehicles such as robotic fish. Consequently, it is highly desirable to conduct research on improving the accuracy of SLAM for the small AUVs.

In spite of the difficulties existing in realizing highly accurate SLAM for AUVs, we believe more and more accurate and robust localization solutions will be achieved in the future with the development of both sensors and SLAM algorithms.

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