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Integrated navigation for autonomous underwater vehicles in aquaculture: A review

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A B S T R A C T

Aquaculture is the world's fastest growing sector within the food industry, supplying humans with over half their aquatic products. Water quality monitoring or cage inspection is an indispensable part in aquaculture and is usually done manually. Autonomous underwater vehicles (AUVs) are increasingly being used in aquaculture as technology advances and the cost reduction. Autonomous navigation is considered as a basic function of AUVs but is a challenging issue primarily due to the attenuated nature of electromagnetic waves in water and unstructured underwater environments. An inertial navigation system (INS) is usually selected as the core navigation equipment for AUV navigation because it never fails to measure. This paper reviews and surveys the latest advances in integrated navigation technologies for AUVs and provides a comprehensive reference for researchers who intend to apply AUVs to autonomous monitoring of aquaculture. Pure INS has difficulty obtaining long-range precision navigation due to the inherent error accumulation of inertial sensors over time; aiding inertial navigation systems with auxiliary sensors are common means to improve the navigation accuracy of an INS for AUVs. The survey is conducted according to different assisted navigation technologies for inertial navigation. Finally, the future challenges of the AUV navigation are also presented.

Contents

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1. Introduction

Aquaculture is one of the fastest growing sectors of global food production, providing more than half of the aquatic products to humans [1]. Aquaculture refers to the cultivation of aquatic products such as fish, shrimps, crabs, shellfish, molluscs and algae under artificially controlled conditions. Due to human activities, the environmental pollution, the agricultural production, etc., it may cause changes in the temperature, dissolved oxygen, pH and other environmental factors of the aquaculture water, which affects the growth of aquatic products [2]. Therefore, real-time monitoring of water quality parameters is an indispensable part in aquaculture. Common methods for water quality testing in aquaculture include chemical methods and instrumental methods. The chemical method can qualitatively and quantitatively analyze the water quality, but its detection cycle is long, the operation is complicated, and the automation level is low. The instrument method is that the operator uses the instrument to test the water quality parameters, the instruments used are mostly portable, simple to operate, and can be quickly detected [3], but the detection points are limited, and it is difficult to achieve stereoscopic monitoring of the aquaculture water body. In deep-water cage culture, fish escapes due to the breakage of cage nets can significantly increase farming costs [4], so it is necessary to monitor the net holes.

Most of the detection procedures including water quality testing as well as net pen inspection and management tasks in aquaculture are performed today by the experienced professional, which is time-consuming and increases operational cost and health risk of employees [5]. The use of modern technology to reform the traditional aquaculture industry is of great significance for improving the efficiency and quality of the aquaculture. With technological advances, autonomous underwater vehicles (AUVs) have gradually played a key role in marine development [6]. AUVs have the power source and intelligent control system that can efficiently perform scheduled tasks with its own decision-making and control capabilities. At present, AUVs are mostly employed in survey applications with larger areas of sea. The use of AUVs as a carrier platform to achieve monitoring of aquaculture water quality parameters or cage netting inspection through load sensors is a practical solution.

Because the marine environment is unstructured and hazardous, the development of AUVs will face many challenging scientific and engineering problems, and researchers have made great efforts to overcome these problems so far [6,7]. The progress in new materials, sensor technology, computer technology and advanced algorithms has greatly contributed to research and development activities in the AUV community. Navigation is one of the key AUV technologies because the localization, path tracking and control of the vehicle are all based on precise navigation parameters. Some navigation methods commonly used for land and air are not suitable for underwater because of the attenuation effect of water on electromagnetic signals, and underwater navigation has become a challenging issue in AUV research [7,8]. Among the many underwater navigation systems available, the inertial navigation system (INS) using inertial sensors typically acts as the central navigation system of AUVs because of its autonomy.

Generally, the INS contains an inertial measurement unit (IMU), which consists of accelerometers measuring linear acceleration and gyroscopes measuring angular velocity, the accelerometers and the gyroscopes are usually made up of three mutually perpendicular accelerometers and three mutually perpendicular gyroscopes, respectively. For inertial navigation, the instantaneous speed and position of the vehicle are obtained by integrating the measured values of the accelerometers and gyroscopes. The errors of the IMU increase with increasing elapsed time due to the drift of accelerometers and gyroscopes. Theoretically, the velocity and heading errors accumulate linearly over time, and the position error accumulates exponentially over time [9]. Therefore, the INS can provide relatively accurate navigation information within a short time, but it is physically impossible for a pure inertial navigation system to maintain the high-precision level throughout a mission. Aiding the INS with external information or measurements is an effective means of improving navigation accuracy and has been widely used. In AUVs navigation, auxiliary sensors or other navigation systems, such as a Doppler velocity log (DVL), compass, pressure sensor, global positioning system (GPS), acoustic positioning system (APS), or geophysical navigation system, are usually combined with the INS to form an integrated navigation system [10,11].

The AUV with multi-parameter water quality sensors enables monitoring of aquaculture water quality parameters in accordance with planned routes. In the cage inspection, it is necessary to estimate the position of the AUV with respect to the net pen. In order to achieve the above functions, the AUV must have accurate navigation and positioning capabilities, and integrated navigation is an effective means to achieve high-precision navigation of AUV. This paper aims to summarize and survey the AUV integrated navigation technologies, and to provide a comprehensive reference for researchers who intend to apply AUV to autonomous monitoring of aquaculture. The integrated navigation system using inertial navigation is built in terms of the different auxiliary navigations used; the survey was also conducted in accordance with this idea.

The remainder of this paper is organized as follows. Section 2 briefly describes inertial sensors and two categories of inertial navigation systems. Section 3 summarizes INS/GPS integrated navigation. Research on INS/DVL integrated navigation is reviewed in Section 4. Section 5 introduces the integrated navigation combining INS with APS. The research progress of the integrated navigation combining INS with geophysical navigation is reviewed in Section 6. Future challenges for AUV navigation are presented in Section 7. The last section gives conclusions.

2. Brief introduction to inertial navigation

2.1. Inertial sensors

Inertial sensors consist of two types: the gyroscope and the accelerometer. In inertial navigation, gyroscopes and accelerometers can be combined to estimate a vehicle's navigation parameters including the attitude, velocity and position. The principle of INS is relatively simple, however, the inherent errors of the gyroscopes and accelerometers will cause the positioning error of the vehicle to diverge [12]. For longer underwater navigation, the limited accuracy of inertial sensors has become a major constraint in improving the performance of INS.

2.1.1. Gyroscope

In integrated navigation of AUVs, optical gyroscopes such as ring laser gyroscopes (RLGs) and fibre optic gyroscopes (FOGs), and micro-electromechanical systems (MEMS) gyroscopes are widely used. RLGs and FOGs are both based on the Sagnac effect [13]. The laser beam in an RLG is passed through a series of mirrors in different directions. The angular rate is determined by the phase change of the laser that has passed through the mirrors. Compared to an RLG, the laser beams in an FOG are propagated around optical fibre rather than a closed path using mirrors. Compared with the mechanical gyro, the optical gyroscope has no moving parts and can be started up within a few seconds. Optical gyroscopes can attain a relatively accurate angular rate. The length of the light transmission path is a key parameter in determining the accuracy of an optical gyroscope, in general, the accuracy is proportional to the length. Typically, RLG and FOG have an angle drift rate of about 0.1–10° per hour [14].

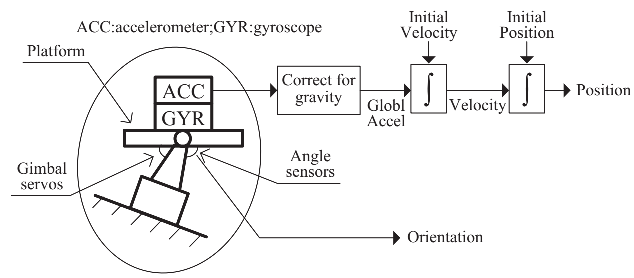

Fig. 1 – The PINS schematic diagram.

MEMS gyroscopes utilize the Coriolis effect. The gyroscope rotation creates a vertical Coriolis force on a suspended vibrating mass that determines the angular rate of the gyro [7]. At present, MEMS gyroscopes are less accurate than optical gyroscopes; however, MEMS gyroscopes built using silicon micro-machining techniques have smaller sizes, exhibit lower power consumption, and are relatively inexpensive to manufacture.

2.1.2. Accelerometer

Accelerometers for inertial navigation use Newton's second law to measure acceleration (a). Newton's second law is expressed by the formula $F = ma$, where F represents an external force and m is called the "proof mass" [15]. Accelerometers include the categories of mechanical accelerometers and solid-state accelerometers from the structure. A mechanical accelerometer contains a suspended mass. Solid-state accelerometers can be divided into vibratory, surface acoustic wave and silicon accelerometers. MEMS accelerometers, which employ the same principle as mechanical and solid-state accelerometers, are manufactured using silicon micro-machining technology [16].

2.2. Inertial navigation system

Structurally, the inertial navigation system is divided into platform inertial navigation system (PINS) and strap-down inertial navigation system (SINS). The main difference between the two categories is the reference frame for inertial sensors operation. In the platform type system, the gyroscopes and accelerometers are fixed on a physical platform that is isolated from any external rotary motion [17]. The platform is mounted by gimbals that allow the platform freedom in three axes; gyroscopes mounted on the platform are capable of detecting the rotation of the platform, and the rotation is fed back to a torque servo that can drive the gimbal to can-

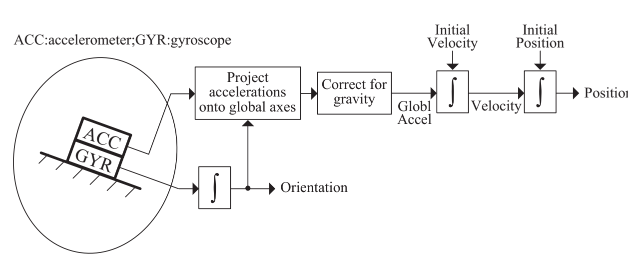

Fig. 2 – The SINS schematic diagram.

Table 1 – The range of the constant bias of inertial sensors used in this paper.

Data Source	Gyro Bias	Acce Bias	References
IMU	0.003°-3°/h	0.01–4 mg	[29,30,31,32,37,46,47,50,51,53,54,62,63,64,69,72,77,80,91,96]
Simulation Assumption	0.01°-3°/h	0.05–3 mg	[25,26,33,38,40,45,49,55,68,71,81,82,102,103]

cel out this rotation. Thus, it is possible to keep the platform aligned with the global frame. To track the device orientation, angle sensors can be used to measure the angles between adjacent gimbals. The position of the device is obtained by double integration of the signals from accelerometers. It is necessary to consider the influence of vertical gravity on the acceleration before the integral calculation [16]. The PINS schematic diagram is shown in Fig. 1.

In the SINS, the inertial sensors are mounted rigidly on the device. The output signals of gyroscopes are integrated to track orientation. Taking into account the known orientation, the accelerometer signals are decomposed into global frame, and then the obtained global acceleration signals are double integrated to track position [18]. Fig. 2 shows the SINS schematic diagram. The strap-down system has low mechanical complexity and tends to be a smaller size compared to the platform system, while the SINS has a high computational complexity.

Inertial navigation is a fully autonomous navigation that does not receive external signals or transmit signals to the outside. The SINS is characterized by its small size, light weight and low cost compared to the platform INS, which is widely used in AUV navigation. Over the past several decades, the SINS has gradually become mainstream [8,19]. The development of inertial technology has significantly enhanced the performance of accelerometers. However, improvements in the mechanical gyroscope and optical gyroscope performance are relatively slow. Recently, the atomic gyroscope has developed rapidly, which can obtain higher precision with respect to mechanical or optical gyroscopes [20]. The data provided by inertial sensors is only valid in the short term. Therefore, in addition to inertial sensors, the AUV navigation system is usually supplemented by auxiliary sensors with different operating frequencies and precisions [21].

In the following sections, inertial sensor data for AUV navigation experiments are either provided by IMU or are assumed. It is well known that the inertial sensor drift is critical to the INS performance, Table 1 shows the range of the constant bias of gyroscopes and accelerometers used in integrated navigation for AUVs.

3. INS/GPS integrated navigation

On land, GPS is a common means of navigation that can provide absolute vehicle position. However, due to the attenuation effect on radio signals, the GPS receiver cannot be used underwater. The GPS-aided inertial navigation for AUVs is suitable for shallow water applications, in where the vehicle is easy to regularly surface to accept the position fix from GPS [22].

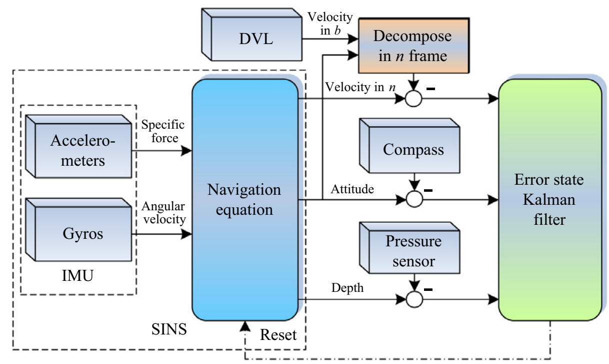

Fig. 3 – SINS/DVL integrated navigation structure.

Yun et al. [23,24] introduced an INS/GPS into a small AUV navigation. An asynchronous Kalman filter was developed to improve position estimation. The test results demonstrate that it is feasible to use a low-cost IMU combined with intermittent reception of differential global positioning system (DGPS) signals to navigate. Ragel and Farooq [25] proposed a DGPS-aided INS for AUV application. Through the interacting multiple model feedback filter, the INS and DGPS data are well integrated to estimate the positon error of the AUV. In [26], radial basis function (RBF) neural network combined with wavelet package analysis is used for data fusion of SINS/GPS integrated navigation, and the positioning accuracy of AUV was significantly improved.

An integrated navigation system with the integrated use of several INS sensors and GPS for AUV applications is described. An adaptive Kalman filter via fuzzy logic is used for position information integration of the INS/GPS and data fusion of the INS sensors. A real sea trial in the *Hammerhead* AUV has shown an enhanced performance of the INS/GPS navigation system [27,28].

INS has long-term drift characteristics, and GPS can provide instantaneous position accuracy of approximately 15–100 m at rate of 1 Hz [29]. Through the integration of INS and GPS, their respective shortcomings can be effectively restricted. Typically, the data fusion method that combines INS output with GPS signals is some form of Kalman filer (KF).

4. INS/DVL integrated navigation

As the drift errors of inertial sensors are inevitable, the output of the pure inertial navigation system diverges over time. There are many optional sensors that can be used to suppress the inertial measurement units (IMUs) drift, among them, DVL is often used to assist the underwater inertial navigation [30].The INS/DVL integrated navigation mainly uses the velocity of DVL to restrain the INS accumulation error. Currently, the integration of INS and DVL has even become a standard configuration for AUV navigation [6].

4.1. *Typical SINS/DVL integrated navigation*

In many applications, the DVL-aided inertial navigation system uses a depth sensor and compass as auxiliary sensors; Fig. 3 shows a typical SINS/DVL integrated navigation structure for AUV. The system framework contains SINS, error state Kalman filter, aiding navigation sensors, such as DVL, compass and pressure sensor [31]. In Fig. 3, the error state Kalman filter is used to estimate the SINS navigation errors. The navigation solution and the navigation error estimates are independent of each other; the navigation error estimates are transmitted to the SINS to reset the navigation parameters. Subsequently, the corrected navigation parameters are used as recent initial conditions of the navigation equations [6,31].

Doppler sonars can measure the velocity of the carrier relative to sea bottom. The Doppler velocity log is often used for near-bottom navigation of AUV [14]. Uliana et al. [32] developed a Doppler-assisted INS using a Kalman filter for calculating the heading and position of an AUV named SARA. By periodically rotating the IMU relative to the AUV, the observability of the Kalman filter states was improved, thus optimizing the filter performance. Aiming at optimizing the performance of the navigation system for AUV, I. Klein and R. Diamant [33] utilized the observability Gramian approach to analyze observable and unobservable error states of the DVL-aided INS; the analytical conclusions are verified by numerical simulations. Larsen [34] introduced a Doppler-inertial navigation system with an RLG and a DVL as the core, and the navigation accuracy was confirmed by field tests. The HUGIN 1000 AUV can continuously perform underwater navigation missions utilizing a SINS/DVL navigation system. Sea trials show that the velocity accuracy of DVL and mission pattern affect the positioning accuracy of the AUV [31,35].

Sheijani et al. [36] designed an underwater integrated navigation system based on an indirect Kalman filter. Structurally, an indirect Kalman filter comprises feedforward KF and feedback KF; their performance was discussed using real data provided by inertial sensors, DVL, gyrocompass and depth gauge. From the experimental results, the root mean square error of the position using feedback KF is much lower than that using feedforward KF. Therefore, the feedback structure is more suitable for the navigation occasion with low-cost inertial sensors. Xu et al. [37] applied the evolutionary artificial neural network to a fault-tolerant adaptive KF algorithm to improve the performance of a navigation system, which consists of an SINS, a DVL and a magnetic compass for AUV. It can be seen from the prototype experiments that the scheme is obviously superior to the traditional KF when observation data fail for a short period.

A receding horizon Kalman filter (RHKF), which incorporates the receding horizon strategy into the KF, was used for a velocity-aided INS for AUV. Numerical simulations confirm that the RHKF is more robust than the KF in resisting temporary bounded disturbances to the underwater navigation system [38,39]. A receding horizon H_∞ filter ($RHH_\infty F$), which combines an H_∞ *a priori* filter with the receding horizon strategy, was introduced into a velocity-aided underwater INS. Numerical simulations demonstrate that the $RHH_\infty F$ has higher robustness for the AUV navigation compared with the H_∞ *a priori* filter [40].

International Submarine Engineering Ltd. (ISE) and the Defense Research Establishment Atlantic developed an autonomous navigation system consisting of an IMU and Doppler sonar speed sensor for an AUV named Theseus, and the navigation accuracy exceeds 0.5% of the distance travelled [41,42]. The Deep-Sea Cruising AUV named URASHIMA uses the inertial navigation system combined with DVL. A navigation algorithm using neural networks has been proposed to enhance the navigation performance, and simulation results confirmed the effectiveness of the algorithm [43]. JAMSTEC developed a compact INS with high performance for small AUVs; the performance of the INS combined with DVL has been verified in an AUV sea trial [44].

Krishnamurthy and Khorrami [45] proposed an AUV integrated navigation system consisting of navigation sensors involving MEMS-based inertial sensors, a DVL, a pressure sensor and a 3-axis magnetic compass. The Unscented Kalman Filter was used to provide the state estimation for the AUV and the sensor parameters estimation. Numerical simulations have confirmed the performance of the proposed system. Shabani et al. [46] presented an asynchronous direct KF for the underwater navigation system composed of SINS along with a DVL, depth sensor, and inclinometer. In contrast to the indirect KF, the forecasting procedure is performed in the SINS loop, and the correction procedure implements asynchronously out of the SINS loop. The results of the lake test confirm the effectiveness of the method in improving the navigation performance. Shabani and Gholami [47] reported a SINS supplemented by DVL and depth sensor using the unscented filter as a data fusion tool for AUV, the experimental results verify that the method proposed improves the positioning accuracy of the vehicle compared with the traditional error state Kalman filter.

Li et al. [30,48] constructed a navigation system for a hybrid AUV using an IMU, a DVL and depth sensors. The effect of DVL dropout on the INS has been researched by the post-processing of navigation sensors data. The performance of DVL-assisted SINS is improved significantly with respect to pure SINS, however, for the DVL with water-track or using a relative log, the influence of the ocean current should not be neglected. Considering the influence of the real-time sea current, a DVL aided SINS for AUV was proposed, and simulation results demonstrate that the SINS/DVL has a higher positioning accuracy than pure SINS [49]. A tightly coupled method was introduced into the DVL-aided INS for an AUVFest. The proposed method enhances the adaptability of the DVL to environments. Experimental results show that sporadic measurement failures of the DVL have little effect on the navigation accuracy [50].

The cross-noise existing in the SINS/DVL will reduce the navigation accuracy of AUV; a Kalman filter is used to deal with the cross-noise problem, and the AUV navigation performance is improved after processing the cross-noise [6]. Li et al. [51,52] introduced a backtracking alignment scheme into the navigation system consisting of an INS and a bottom lock DVL for AUV. By using the alignment scheme, the AUV can perform a mission in the AUV alignment process. Moreover, a novel INS error model was derived to reduce the data volume recorded by the backtracking method. Experimental results show that the system positioning error is within 0.3% of the distance travelled.

To improve the alignment accuracy of DVL-aided SINS for AUV, Li et al. [53] applied the covariance-matching method to the Adaptive Unscented Kalman Filter (AUKF). From experimental results, the algorithm is effective for in-motion alignment with large misalignment angles. In [54], by using DGPS signals to calibrate misalignments between INS and DVL as well as the scale factor error of DVL, the navigation accuracy of the INS/DVL for AUV was improved. Furthermore, an iterative implementation was proposed to reduce the AUV attitude error derived from the INS initial misalignment. The DVL velocity accuracy is critical to the positioning accuracy of DVL-aided SINS, Zhao et al. [55] introduced a velocity tracing scheme to restrain the sudden noise and random noise in DVL velocity, and simulation results demonstrate that the level positioning accuracy of the SINS/DVL for AUV is improved.

4.2. *SINS/DVL based integrated navigation*

In underwater navigation, DVL is commonly installed in the bottom of AUV. The DVL malfunctions in the case of large rolls and pitches of AUV. In addition, the data update rate of DVL is low, and DVL usually works in a specific underwater environment, therefore, the application of DVL is occasionally limited. In many underwater missions, the SINS/DVL is usually combined with DGPS, ultrashort baseline (USBL) or other aiding means to enhance the navigation performance and reliability.

An integrated navigation system combining INS and DVL for an AUV named Urashima is presented, in which the feedback gain provided by the Kalman Filter is applied to the velocity error caused by INS and DVL. When the DVL becomes invalid in the water, the system uses only the INS output; therefore, it is more reliable than a dead reckoning system using the DVL. Furthermore, a homing sonar and an acoustic receiver are used as navigation assisting devices to further improve the navigation accuracy [56–58]. An SINS/DVL navigation system considering range measurement for AUV was proposed. Two measurement models based on acoustic range sensors were derived and augmented to the DVL-assisted SINS, respectively. Simulation results with experimental data demonstrate the improvement of the navigational performance and the robustness of the system to the dropout of acoustic sensor signals [59–61]. Considering sea current estimation, DVL with water-track is integrated with the INS by providing velocity aiding. Experimental results using real AUV data show that the accuracy and robustness of the integrated navigation system are significantly enhanced [62]. The integration of IMU, DVL, and USBL is used for the Pirajuba AUV navigation, and the fusion of sample data given by the aforementioned sensors is accomplished through an Asynchronous extended Kalman filter (EKF). The simulation results indicate that the estimates of the AUV position and attitude are fairly accurate [63].

Grenon et al. [64] presented a low-cost INS assisted by a DVL and the Differential Global Positioning System for an AUV named Morpheus. An EKF and a complementary filter were used for the position estimation and the attitude estimation of the AUV, respectively. Preliminary test results confirm that the position error is 0.1% of the distance travelled over an hour. McEwen et al. [65] introduced an ALTEX class AUV operated in the Arctic. The navigation equipment of the AUV mainly consists of an INS with ring-laser gyroscopes, a DVL and a GPS; the navigation device was tested on deck, in open water and under ice, respectively. Test results have proven that the INS/DVL was accurate and reliable. The MBARI Mapping AUV can provide high-resolution images of the deep seabed and shallow underground structure with data from an RLG-based INS supplemented by a DVL sonar. On the surface, the INS regularly accepts GPS fixes. The real-time positioning error of the system is 0.05% of the distance travelled [66]. A Gavia class AUV for the Arctic ice cap underside investigations was equipped with an INS/DVL module that can provide tens of centimetres of positioning accuracy and a drift rate of approximately 1 m per hour. Once the Gavia AUV floats on the surface, GPS signals are sent to the INS to provide position correction [67]. Ben et al. [68] estimated the ocean current model parameters using an SINS/DVL/GPS integrated navigation method; then, the ocean current speed relative to the seabed was obtained, and the DVL got a more accurate velocity relative to the sea floor which is used to assist the SINS by considering the ocean current speed. Hegrenaes and Hallingstad [69,70] proposed a kinetic vehicle model which provides external velocity to assist INS for AUV. The EKF was chosen to fuse the model output and measurements of DVL and USBL. Experimental results through several case scenarios confirm the feasibility of the model-aided INS with only an addition of software.

DVL is a commonly used aiding source for the INS; however, the DVL must lock the sea floor to measure the AUV velocity, and DVL will fail to work in the mid-water zone or on a very rough seabed owing to the loss of bottom track. In some underwater missions, the SINS/DVL requires additional aiding to perform more precise and reliable navigation. Similar to inertial navigation, the DVL-aided INS is a dead reckoning positioning system. The SINS/DVL integrated navigation only reduces the growth rate of the position error with time for AUV and cannot alter the cumulative characteristics of the position error over time.

5. Integrated navigation combining INS with APS

The APS is usually used for underwater navigation. APS can determine the AUV position using measurement ranges calculated from the acoustic signals flight time, which requires additional transponders that are mounted at the sea floor or on a mother ship. APS has no position error accumulation in AUV navigation; its accuracy is related to the baseline length and the distance between the APS and the AUV [71]. Long baseline (LBL), short baseline (SBL), and ultrashort baseline (USBL) or super short baseline (SSBL) are representative acoustic positioning methods. The LBL positioning principle is triangulation with at least three acoustic transponders, which are deployed in the mission area. An AUV can be positioned with the LBL technique. For SBL, transponders are installed at both ends of the hull of the mother ship and triangulation is used; the baseline is determined by the size of the mother ship. The USBL method can determine the relative position of an AUV to the mother ship, and the relative distance and orientation are solved by time of flight (TOF) and the phase difference of an acoustic pulse arriving at different receivers on the bottom of the mother ship, respectively. The LBL is mainly limited by the cost and the time related to deploying and recovering acoustic transponders as well as calibrating the positions of the transponders. The positional accuracy of SBL is related to the baseline size, that is, the size of the mother ship. USBL is easy to operate and easy to use. However, LBL is more accurate than USBL [7,72]. In the AUVs navigation, APS can provide an initial position to be transmitted to INS; thus, long-term drift of the INS can be suppressed.

Willumsen et al. [73] proposed an INS/DVL navigation system that combines a single transponder, the measurements of the transponder, such as range, direction and speed, are utilized to assist the inertial navigation system for AUV. Simulation results show that the navigation performance is dependent on the vehicle's trajectory and state update algorithm. Lee et al. [71] applied two range measurements from acoustic transponders to correct cumulative errors of a strap-down IMU. The simulation results based on the 6-DOF (degree of freedom) nonlinear numerical model are satisfactory. In [74–76], the SSBL estimation was combined with calculation results of an INS to accurately estimate the AUV position. Both the SSBL estimation and the INS information transmission were all based on spread spectrum acoustic signals. Two algorithms for integrating the SSBL and the INS were proposed: one estimated the drift error of the INS output with KF, and the other considered both the SSBL estimation error and the INS error using EKF. Hegrenaes et al. [77] reported navigation results obtained with the underwater transponder positioning (UTP) assisted INS for a HUGIN 1000 AUV; both in situ and post-processing results demonstrated the feasibilities of UTP aiding in large range of autonomous navigation.

Watanabe et al. [78] proposed an acoustic aided navigation scheme for AUV, in which the velocity and position of the support ship measured by the GPS were transmitted to the AUV via the acoustic signal; the inverted USBL (IUSBL) was used to estimate the AUV position relative to the support ship. Then, the INS, the output of the IUSBL, and the acoustic signal were integrated by EKF. The simulation results showed that the INS position error was approximately 1 m with respect to the initial error of approximately 100 m. In [79], a low-cost navigation system including an INS/USBL and a transponder for AUV was addressed. Preliminary harbor experimental tests were performed to verify the effectiveness of the acoustic positioning system using advanced signaling techniques.

In [80], a strap-down INS aided by LBL, ADCP (acoustic Doppler current profiler), and a depth meter for AUVs was proposed. With EKF, different navigation sensor data was fused. Numerical simulations showed that the horizontal positioning error of the AUVs is less than 10 m. Zhang et al. [81,82] researched an AUV positioning system using the interactive aid between SINS and LBL. On one hand, positioning results provided by SINS can improve LBL positional accuracy, on the other hand, LBL locating information can also compensate cumulative errors of SINS regularly and effectively. Chen et al. [83] applied the Bayesian smoothing algorithm to an LBL assisted INS, and the implementation results indicate that the proposed scheme has better accuracy and reliability compared with the traditional EKF. IXSEA independently developed its inertial and acoustic technologies; inertial sensors and the acoustic positioning system have their own advantages and shortcomings. High-performance navigation solutions can be provided to the users by combining inertial and acoustics technologies [84]. Aiming at strengthening the performance of the INS/LBL navigation system for the deepwater AUV, a multi-model EKF algorithm was proposed; actual data test results verified the effectiveness of the algorithm [85].

The APS estimates the absolute position of underwater vehicles, which is applicable to restricting the error growth of INS. Therefore, the combination of INS and APS can significantly improve the AUV navigation accuracy. However, the APS requires additional transponders which are deployed on the seafloor or mounted on a mother ship, and the transponders are difficult to install. In this navigation method, the AUV must be operated within the coverage range of the transponders, so its mission area is limited.

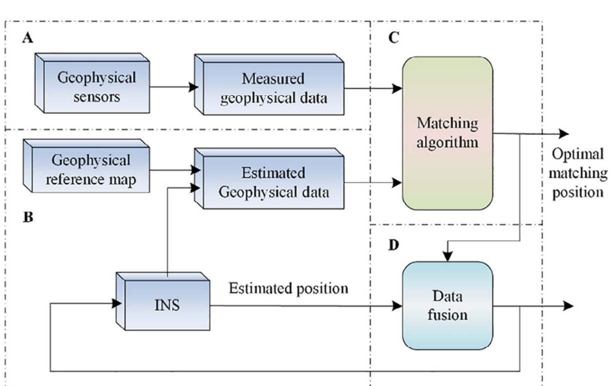

Fig. 4 – Principle diagram of geophysical navigation assisted inertial navigation.

6. Integrated navigation combining INS with geophysical navigation

An integrated navigation system composed of INS and geophysical navigation, which uses inertial navigation as its core, can achieve high-precision navigation by correcting the cumulative error of the INS in real time using the geophysical field within travelling range of the underwater vehicle. The principle diagram of the geophysical navigation assisted inertial navigation is shown in Fig. 4. In Fig. 4, the measured geophysical data are obtained using geophysical sensors mounted on the vehicle (see Fig. 4A); meanwhile, according to the estimated position provided by the INS, the estimated geophysical data are achieved from an existing geophysical reference map (see Fig. 4B); then the measured geophysical data and the estimated geophysical data are transmitted to the navigation computer, the optimal matching position of the vehicle is determined by the matching algorithm (see Fig. 4C); thus, through fusing the INS position and the optimal matching position, cumulative errors of the INS can be effectively corrected and the navigation performance of the INS is improved (see Fig. 4D). Geophysical navigation mainly consists of terrain matching navigation, geomagnetic matching navigation and gravity matching navigation.

6.1. *Integrated navigation combining INS with terrain navigation*

For long-duration underwater operations, the position error of the INS needs to be corrected using the absolute position. GPS is invalid in the underwater environment, and APS requires the time-consuming pre-deployment and position calibration of acoustic transponders, so terrain-based navigation is a suitable alternative for underwater navigation. In general, terrain navigation obtains a position estimate by comparing terrain measurements with an existing topographic map. Underwater terrain matching navigation has no cumulative errors, so it can be used to periodically calibrate the INS error [85]. Compared to other geophysical navigation, the terrain matching navigation is by far the most mature geophysical navigation technology.

The trajectory recovery from fusion of the INS and a forward-looking sonar for terrain aiding was discussed for an AUV named NTU-UAV. By periodically resetting the errors of inertial sensors, considering the sonar alignment information in the world frame, the IMU combined with the vehicle model can achieve precise attitude estimation [86]. Anonsen et al. [87] focused on a terrain-aided INS for submerged navigation. An improved filter model was introduced into Bayesian terrain navigation of AUV. Tests based on actual data showed that the model mentioned yielded smoother and more accurate estimates compared to conventional filter models. Terrain relative navigation (TRN) is applicable to the AUV positioning due to its drift-free characteristics, in [88], a low-cost TRN system was proposed using both lower-accuracy INS and low-cost altimeters, the effects of translational and attitude uncertainty caused by both the inertial sensors and the altimeters on the system performance were analyzed, and the theoretical results were demonstrated by field trials of the Dorado AUV. Nygren [89] introduced the terrain-aided navigation system for AUVs, which was incorporated with an INS. A finite difference filter is applied to the terrain navigation module to address the AUVs positioning in flat bottomed areas. The position estimate, which is provided by the terrain navigation system, is utilized to smooth cumulative errors of inertial sensors, so the position error of the INS can be bounded.

Nakatani et al. [90] proposed a terrain based localization scheme for an AUV named TUNA-SAND with a profiling sonar. The terrain localization results were fused with the estimations of the INS/DVL using the Particle Filter. Simulation results using collecting data demonstrate the real-time and robustness of the scheme. A particle filter-based terrain navigation method aimed to correct drift errors in an AUV INS was developed and tested, and the results illustrate that the MARV AUV can continuously obtain a position fix during a long-distance mission [91,92]. A type of terrain navigation system used to provide submerged position updates for the INS mounted on the HUGIN AUV was described. A real-time map generator to build a local map was implemented; therefore, the vehicle was able to build its own map during the mission, and the map was used to obtain position fixes when returning to the mapped area. In the sea trial, the actual navigation error dropped from more than 50 m to approximately 10 m when re-entering the previously mapped area [93]. A terrain based navigation system with low-cost navigation sensors for an AUV was proposed. The navigation algorithm was based on particle filters; the influences of different parameters in the particle filter on the performance of the navigation algorithm were also discussed [94]. Chen et al. [95] applied the least squares estimation algorithm to the underwater terrain positioning for AUV, and the Fisher quadratic discriminant method is also introduced to reduce the influence of pseudo positioning points on the positioning accuracy in flat terrain areas, simulation tests show that drift errors of the INS can be effectively restrained.

6.2. *Integrated navigation combining INS with geomagnetic navigation*

Geomagnetic-map-based navigation relies on comparing an existing map with on board magnetometer measurements to provide position fixes and bound the position error growth of an INS. The integrated navigation system composed of an INS and magnetometers is completely passive, which meets the need of covert navigation.

Wu et al. [96] introduced an experimental evaluation of a geomagnetic assisted INS for AUV. The measured geomagnetic field values were compared to an *a priori* field map to reduce INS position errors. A novel matching algorithm using the interval knowledge of the geomagnetic field measurements was presented, and the effectiveness of the matching algorithm was validated using real AUV data. Geomagnetic assisted inertial navigation is an ideal autonomous navigation method for AUV due to its advantages such as concealment, stability and high precision. The iterated closest contour point (ICCP) algorithm applied to the integrated navigation system was analysed, and the simulation results verified the improvement in the long-range navigation accuracy in the INS [97]. Zheng et al. [98] presented a gravity-geomagnetism combined assisted navigation (GGCAN) method for correcting INS errors of AUVs. The optimal position estimations of gravity assisted navigation and geomagnetic assisted navigation were obtained separately by the multi-model adaptive estimation. Then, according to the principle of optimal weight allocation, those estimations were combined using the weighted average method. Simulation results confirm that the GGCAN method improved the accuracy and reliability of INS.

6.3. *Integrated navigation combining INS with gravity navigation*

An alternative method for correcting INS accumulation errors is to use the gravity aided navigation. For gravity-matching

Table 2 – Data fusion algorithms of inertial navigation-based integrated navigation systems.

Data Fusion Algorithm	Description	References
Kalman filter	Applicable to a linear system, state variables of the system assumed to be Gaussian distribution.	[23,24,25,27,28,29,30,32,34,36,44,46,48,50,51,52,54,56,57,58,62,65,67,68,69,70,74,76,77,81,84,98,103]
Extended Kalman filter	Extension to the Kalman filter, estimating the state of a nonlinear system using first-order Taylor series expansion.	[27,28,31,33,35,49,59,60,61,63,64,71,72,73,74,78,79,80,83,85,102]
Unscented Kalman filter	Instead of linearizing a non-linear system, using minimal sampled sigma points to obtain the mean and covariance estimates of state variables.	[45,47,53,73,101]
Particle filter	Nonparametric representation of state distribution. Using a few particles with associated weights to estimate the probability distribution for state variables.	[87,90,91,92,94]
Federated Kalman filter	Adopting two-level filter structure. Subsystems first use Kalman filter for data fusion, and then the estimates from the subsystems are further fused in the federated Kalman filter.	[55,82]
Receding horizon Kalman filter	Combining Kalman filter with receding horizon strategy.	[38,39]
Receding horizon $H\infty$ filter	Combining an $H\infty$ a priori filter with the receding horizon strategy.	[40]
Fault-tolerant adaptive Kalman filter	Combining Kalman filter with neural network, strengthening the fault-tolerant of Kalman filter.	[26,37]

navigation, gravity maps need to be drawn in advance, in which each route has a special gravity distribution. At present, the gravity sensor is still difficult to use for real-time measurements of the earth gravity.

To enhance the inertial navigation accuracy and reduce the dependence on GPS, Lockheed Martin has successfully applied gravimeters and gradiometers to the gravity-assisted inertial navigation system. In the gravity navigation algorithm, an EKF was used to estimate the navigation errors [99,100]. A self-adaptive unscented KF (SA-UKF) was used in the underwater gravity assisted navigation system; with the algorithm, the INS navigation error can be effectively corrected, and the AUV position can be accurately obtained [101]. In [102], a local gravity potential model was introduced into the observation equation of INS, the inertial errors can be estimated directly using an EKF. The simulation results demonstrate that the INS positioning errors can be effectively constrained. Han et al. [103] proposed an improved terrain contour matching algorithm (TERCOM) for gravity-aided inertial navigation, using the shortest path algorithm and the novel correlation analysis method, the real-time performance and matching accuracy of the TERCOM algorithm are improved; simulation experiments on a gravity anomaly grid map indicate that the algorithm reduces effectively the accumulative error of the INS.

The geophysical navigation errors do not accumulate or diverge over time, so this type of navigation has high accuracy, and making it an ideal aiding source for INS. The main components of geophysical navigation are an existing geophysical reference map, geophysical sensors and a matching algorithm. It is crucial for geophysical navigation to attain a high-quality geophysical reference map in advance. For long-distance AUV navigation, the integration of inertial navigation and geophysical navigation is the only feasible method to ensure accurate navigation.

In this paper, data fusion algorithms of the inertial navigation-based integrated navigation systems for AUV are shown in Table 2. In Table 2, the Kalman filter is a linear filter suitable for linear-Gaussian problems, however, the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and the particle filter (PF) are nonlinear filters. The EKF is the most widely used nonlinear filtering approach, which is based on a simple linear approximation to the nonlinear equations. In systems of a highly nonlinear nature and non-Gaussian noise sources, the UKF and the PF, which keep the nonlinear nature of the problem, may significantly improve system performances. The inherent weakness of these nonlinear filters is that computational complexity usually grows exponentially with the dimension of the state vector being estimated. The federated filter is a two-stage filtering architecture, first, all the parallel local filters combine their own sensor systems with an inertial system to obtain the local estimates of the system states. These local estimates are subsequently fused in a master filter to achieve the global estimation. In general, the computational load of the federated filter can be significantly reduced, but at the cost of lower estimation accuracy. If there is a lack of accurate noise statistics, the adaptive filter can be used to optimize the filter parameters that reflect the noise properties. Combining the filtering algorithm with the receding horizon strategy can improve the performance of the integrated navigation system, such as the receding horizon Kalman filter and the receding horizon $H\infty$ filter.

7. Future challenges

Due to harsh and unstructured underwater environments, autonomous navigation of AUVs is a challenging issue. Visual simultaneous localization and mapping (VSLAM) is a new navigation and positioning technology in recent years, and has become a hotspot in the research of autonomous navigation of land-based robots. Due to the complexity of the underwater environment, combining VSLAM technology with inertial sensors to achieve high-precision autonomous navigation of AUV is a challenging research topic. With the developments in both the technologies and algorithms of integrated navigation, improved AUV navigation will continue to make new missions available that were previously considered impractical or infeasible.

The precision of the INS based on optical gyroscopes is proportional to the size of the optical gyroscopes; therefore, the size of the INS will also become larger to improve the navigation accuracy. Recently, the demand for small AUVs has been increasing due to their lower costs and good operation efficiency. However, a large INS cannot be applied to small AUVs considering payloads, power consumption and cost. Therefore, developing a small, high accuracy, low power consumption and low cost INS is a challenge for the small AUVs.

Shallow-water navigation for AUV has been effectively solved by INS combined with GPS, and the INS/DVL navigation system is typically used for the near seafloor navigation of AUVs. However, obtaining high-precision navigation in the mid-depth region of the ocean is a challenging issue due to the lack of effective sensors.

So far, the development of state estimators for AUV integrated navigation has mainly focused on mathematical analysis and experimental evaluation in post-processing. The implementation of estimators in situ can significantly promote the underwater vehicle navigation. Currently, when some nonlinear filtering algorithms such as UKF and PF (particle filter) are used for the state estimation of an integrated navigation system, it is difficult to theoretically analyze the performance of these filter algorithms; thus, the stability of these algorithms in practical applications cannot be guaranteed.

The reference map for geophysical navigation is usually described using a grid or spherical harmonic series, such as a digital elevation model and an international geomagnetic reference field (IGRF) model. However, the spatial resolution of geophysical parameters approximated by spherical harmonic series tends to be lower, and match navigation based on the grid model not only easily misses reference image information between different grids but also can not indicate the error of the reference map deviating from the true value on a single grid.

8. Conclusions

The underwater monitoring operations of traditional aquaculture are mainly done manually, with high labor intensity and high risk. Unmanned underwater vehicles (UUVs) become less and less expensive, following also the trend for smaller size and flexibility, which are increasingly being used in aquaculture. Different from conventional remotely operated vehicles (ROVs), AUVs require several key technologies to achieve their missions such as autonomous navigation, path planning, motion control, and system architecture; underwater autonomous navigation technology is the basis for localization, path tracking and autonomous movement of AUVs in aquaculture. AUVs typically use the INS as their main navigation system; however, due to inherent error accumulation of inertial sensors over time, the pure INS has difficulty obtaining long-range precision navigation. Therefore, INS is often combined with other navigation systems or devices such as GPS, DVL, acoustic positioning systems, or geophysical navigation systems to improve the AUV navigation accuracy.

High-precision navigation and positioning capabilities are important criteria for evaluating the AUV performance in aquaculture. The development of integrated navigation systems with high reliability, high integration and comprehensive compensation and correction functions represents a new trend in navigation technology for aquaculture AUVs. With advances in the integrated navigation technology, it is possible to implement new missions that were previously considered difficult to perform for AUVs.

Conflict of interest

The authors declare that there is no conflict of interest.

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