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Editorial

Navigation Control and Signal Processing Methods for Multiple Autonomous Unmanned Systems

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1. Introduction

Autonomous underwater vehicles (AUVs) have been widely deployed in numerous underwater applications, such as biological monitoring, oceanographic surveys, and military underwater surveillance [1–4]. The localization of AUVs has usually been a challenge because of rapid attenuation of the radio frequency, such as global positioning system (GPS) signals. The high-precision accelerometer- and gyroscope-based inertial navigation system (INS) is the most common method of AUV navigation. Nevertheless, the navigation errors of AUVs accumulate over time because of the inertial sensors' drifts [5–8], which may cause unlimited increases in the localization error. The increase in localization errors can be corrected and updated by the GPS signal after surfacing, but it is impractical to surface when AUVs are working during a deep-water mission [9–11].

In the navigation of AUVs, a significant problem is determining the positions of AUVs by using a nonlinear filter. Nonlinear filtering is an effective method for inferring the unknown state of a nonlinear system and has been widely employed in a number of applications involving the navigation of AUVs, signal processing, communications, target tracking, and control [12–19]. A few nonlinear filters for underwater navigation have also been presented to improve the estimation accuracy, such as the extended Kalman filter (EKF), unscented Kalman filter (UKF), and cubature Kalman filter (CKF) [20–25].

The performance of the above filtering algorithms depends largely on a priori knowledge of the noise covariance matrix, and the use of an inaccurate noise covariance matrix can result in substantial estimation errors or even filtering divergence. However, in the navigation of AUVs, an accurate noise covariance matrix is very difficult to establish and may be time-varying, because the performance of sensors may vary with changes in the environment, which will degrade the navigation accuracy [26–29]. The adaptive algorithm is an effective method for solving the inherent problem of unknown noise covariance matrices in the underwater navigation of AUVs [30–35].

In contrast to fully actuated AUVs, underactuated AUVs are equipped with fewer propellers. This configuration offers distinct advantages and unique characteristics. The primary benefit of underactuated AUVs lies in their ability to perform intricate motions and maneuvers using fewer control inputs or actuators. As a result, underactuated AUVs offer simpler and more cost-effective design solutions [36–38]. However, due to their complicated interactions with the underwater environment, underactuated AUVs exhibit inherently nonlinear dynamics. Consequently, controlling such systems requires advanced control techniques to handle nonlinearities and ensure the stability of system.

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From the above analysis, it can be seen that it is easy to be influenced by external disturbances to the nonlinearity characteristics, which brings obvious challenges to the controller design process [39–41]. To ensure the reliable operation of an AUV, it is crucial to model disturbances accurately and account for their effects. DO has gained widespread popularity in the field of control due to its superior performance in estimating uncertainties [42,43]. A DO was developed in [44] to assess the influence of disturbances while optimizing communication resource consumption, and intermittent measurement-based uncertainty was also considered, while the converge speed of estimation errors was ignored. In [45], a novel finite-time DO was proposed, but the upper bound of the convergence time is unknown. In [46], a fixed-time DO was proposed to determine the disturbance, and it was shown that the estimation errors can reach the zero domain within the settling time. An observer-based fixed-time sliding mode control (SMC) was proposed in [47], where a weak chattering DO was designed to estimate uncertainties within a fixed time. However, in most previous works, the upper bound of the disturbance is assumed to be known [48], which is not reasonable under specific conditions. By integrating the DO with the formation controller, this paper proposes a novel approach for underactuated AUV formation control.

Formation control strategies play a pivotal role in the field of unmanned systems, providing theoretical and practical frameworks for coordination and collaboration among multiple unmanned vehicles. Presently, most existing formation control strategies can be roughly categorized into leader–follower, behavior-based, virtual structure, graph theory-based, artificial potential function, and visually based strategies [49]. Among these, the "leader–follower" strategy stands out as one of the most often used and fundamental approaches in formation control. Under this strategy, one or more unmanned vehicles are designated as the leader, whose trajectory serves as a reference for other followers. The leader's movements determine the overall shape and behavior of the formation. Communication and mutual perception between the leader and followers are crucial in maintaining tight coordination within the formation.

The primary challenges associated with controlling underactuated AUV systems can be broadly categorized into three groups [50]. Firstly, in the existing literature [51,52], to simplify the process of controller design, the mass and damping matrices in underactuated AUV models are assumed to be diagonal, while this kind of model cannot reflect the actual conditions due to the inherent lack of symmetry between the bow and stern of the AUV. To overcome this limitation, ref. [53] introduced a coordinate transformation of the design controller. This conventional control design for such models often involves introducing a coordinate transformation which can transform ship dynamics to a "diagonal form" before addressing the coupling effects between the position and velocity variables, which can be cumbersome and time-consuming. Secondly, it is observed that the majority of existing formation control schemes, employing the leader–follower method, rely on velocity information from the leader [54,55]. However, in practical scenarios, measuring the velocity of the leader is challenging for followers due to noise contamination and communication delays. As a result, a more practical and constructive approach for formation control is to rely solely on measurements of positions and orientations, eliminating the need for velocity information [56,57]. Thirdly, an essential performance criterion for formation control is the converge speed. The fixed-time stability technique [58–60] has emerged as a valuable approach for designing a controller which can ensure a guaranteed converging time for the system, irrespective of the initial conditions of the agents. While the concept of fixed-time formation control holds promise, current research efforts have predominantly focused on addressing the consensus problem in general multi-agent systems and fully actuated AUVs, leaving room for further investigation and development in this specific area.

2. An Overview of the Published Articles

This section presents a comprehensive overview of the Special Issue title “Navigation Control and Signal Processing Methods for Multiple Autonomous Unmanned Systems”, summarizing the key contributions of the published articles.

Multi-robot task assignment is one of the main processes in an intelligent warehouse. One of the papers models multi-robot task assignment in an intelligent warehouse as an open-path multi-depot asymmetric traveling salesman problem (OP-MATSP). A two-objective integer linear programming (ILP) model for solving OP-MDTSP is proposed. The theoretical bound on the computational time complexity of this model is O(n!). We can solve the small multi-robot task assignment problem by solving the two-objective ILP model using the Gurobi solver. The multi-chromosome coding-based genetic algorithm has a smaller search space, so we use it to solve large-scale problems. The experimental results reveal that the two-objective ILP model is very good at solving small-scale problems. For large-scale problems, both the EGA and NSGA3 genetic algorithms can efficiently obtain suboptimal solutions. This demonstrates that the paper’s multi-robot work assignment methods are helpful in an intelligent warehouse [61].

Additionally, a localization system is one of the basic requirements for coal mines. Ultra-wideband (UWB), as a technology with broad application prospects, is considered to have great potential in the absence of satellite signals, especially in an underground mine environment, as it can provide rescue assistance. However, state-of-the-art UWB position systems in coal mines cannot efficiently differ the line of sight from all communication links, which results in the deterioration of the localization accuracy. In another paper in this Special Issue, the authors propose an LOS/NLOS classification method based on a deep learning algorithm. Specifically, they utilize the Generative Adversarial Network (GAN) to generate diagnostic data for frame transmission under non-line-of-sight (NLOS) conditions. Then, a Convolutional Neural Network (CNN) is adopted to identify NLOS communication. Finally, the trilateral centroid positioning algorithm (TCPA), based on ranging data, is used to verify the effect of our method for a localization system in coal mines [62].

Another recent study, included in this Special Issue, proposes an improved in-motion coarse alignment method for a strapdown inertial navigation system (SINS) using position loci obtained from the Global Positioning System (GPS). The difference from the popular coarse alignment methods is that the proposed algorithm uses GPS position loci information to form the vector observation and does not need velocity information, which expands the application range of in-motion coarse alignment. In addition, this paper utilizes the Optimal-REQUEST algorithm to reduce the influence of random errors contained in the vector observation. The Optimal-REQUEST algorithm is an adaptive iterative updating algorithm, which can adaptively adjust the gain of the filter according to the loss function. The simulation results confirmed that the proposed algorithm can suppress the impact of random errors effectively. The pitch, roll, and yaw angles calculated by the proposed algorithm were improved by 51.95%, 53.80%, and 63.03% compared with the comparison algorithms [63].

There are various types of autonomous unmanned systems, covering different areas of sea, land, and air and exhibiting significance in multiple fields of national security and social life. Due to the development of technology, the scale of unmanned systems is becoming increasingly large, the number of components in the system is increasing, and the operating environment of the system is becoming increasingly complex. Therefore, the probability of failure of the components of the system will also be significantly increased. In order to eliminate the impact of a fault in time, the fault diagnosis method is significant. Considering the differences in components in autonomous unmanned systems, if a specific fault diagnosis algorithm is designed for each type of component, it will lead to difficulties in the coordinated control of the system. Therefore, another paper analyzes the data characteristics of unmanned autonomous system devices (such as sensors) and finds that these data have time series. Therefore, the data for different devices can be converted into time series, and a general fault diagnosis algorithm that is suitable for most devices can be developed. The fault diagnosis algorithm is based on the clustering algorithm. In order to improve the clustering effect, the time series of different devices are represented by Gaussian mixture clustering to reduce the computational complexity of the clustering calculation. Then, a time series similarity measurement method based on the improved Markov chain is proposed. This method can distinguish normal samples from abnormal samples more successfully in order to classify and identify faults effectively [64].

The wave parameter is an important environmental input condition. Traditional contact wave measurement methods are unable to meet the requirements of high precision, non-contact, and enabling ship wave field assessment. Alternatively, stereo vision technology can realize a non-contact and mobile form of measurement. However, this technology suffers from poor efficiency and adaptability. Another paper in this Special Issue proposes a comprehensive wave measurement method that is based on stereo vision, wherein the gridding of siftGPU is used to achieve the fast matching of large images. The whole algorithm can be run within 6 s and guarantees more than 20,000 feature-matching logarithms. Furthermore, by utilizing the least squares method and sea surface wave surface theory, the sea surface base level can be calculated without control points, along with the inversion of the sea wave parameters (wave height, period, and wave direction) and error point fitting. The rationality and superiority of the algorithm were verified through multiple comparison experiments [65].

Another study addresses the distributed optimal decoupling synchronous control of multiple autonomous unmanned linear systems (MAUSs) that are subject to complex network dynamic coupling. The leader–follower mechanism based on neighborhood error dynamics is established, and the network coupling term is regarded as the external disturbance to realize the decoupling cooperative control of each agent. The Bounded L2-Gain problem for the network coupling term is formulated into a multi-player zero-sum differential game. It is shown that the solution to the multi-player zero-sum differential game requires the solution to the coupled Hamilton–Jacobi (HJ) equations. The coupled HJ equations are transformed into an algebraic Riccati equation (ARE), which can be solved to obtain the Nash equilibrium of a multi-player zero-sum game. It is shown that the bounded L2-Gain for coupling attenuation can be realized by applying the zero-sum game solution as the control protocol, and the ultimately uniform boundedness (UUB) of a local neighborhood error vector under conservative conditions is proved. A simulation example is provided to show the effectiveness of the proposed method [66].

The unmanned operation of agriculture machinery in a full farmland field is an important part of unmanned farm and smart agriculture. Although the autonomous navigation of agricultural robots has been widely studied in the literature, research on the full-field path tracking problem of agriculture machinery is rare. In a paper in this Special Issue, in order to enhance the adaptivity of the path tracking algorithm, an improved fuzzy Stanley model (SM) is proposed based on particle swarm optimization (PSO), where the control gain is modified adaptively according to the tracking error, velocity, and steering actuator saturation. The PSO-enhanced fuzzy SM (PSO-FSM) is verified by experiments on numerical simulation and the self-driving of a mobile vehicle. The simulation results indicate that the PSO-FSM achieves a better result than SM and FSM, where the PSO-FSM changes the control gain adaptively under different velocities and actuator saturation conditions, and the maximum lateral errors of the SM and PSO-FSM for mobile vehicle autonomous turning are 0.32 m and 0.03 m, respectively. When the location of the mobile vehicle deviates from the expected path at 4 m in a lateral direction, the distance of the guided trajectory for the mobile vehicle to reach the expected path is no more than 5 m [67].

In another study, to solve the problems of measurement information abnormal error and nonlinear filtering in UWB navigation and positioning, an ultra-wideband position algorithm based on a maximum cross-correlation entropy unscented Kalman filter is proposed. The algorithm first obtains the predictive state estimate and the covariance matrix through traceless transformation. Then, it reconstructs observation information using the nonlinear regression method based on the maximum cross-correlation entropy criterion, which enhances the robustness of the unscented Kalman filter algorithm for heavy-tailed noise. The simulation and actual test results show that this algorithm has better positioning accuracy and stability than the traditional filter algorithm in a non-Gaussian noise environment. This algorithm effectively solves the problem that the UWB indoor location is easily affected by indoor environments, resulting in fixed deviation for that location [68].

These studies collectively highlight the future of navigation control and signal processing methods for autonomous unmanned systems. Given the breadth of this topic, this Special Issue includes papers from focused research to broad overviews. It is clear that many factors, from cost-effectiveness and the role of people to the importance of different models, will influence the future of this field.

3. Conclusions

Navigation, guidance, control, and signal processing are important for a number of autonomous unmanned systems in ocean exploring, surveying, and so on. However, there are some challenges for autonomous unmanned systems due to the complex underwater environment. The articles published in this Special Issue mainly introduce and discuss how to solve the problems of navigation, control, and signal processing.

Future research should focus on the improvement of navigation, control, and positioning for multiple autonomous unmanned vehicles. Moreover, more state-of-the-art methods such as artificial intelligence, deep learning, and machine learning should be introduced and integrated with traditional navigation and control methods.

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