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High-precision, limited-beacon-aided AUV localization algorithm

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A B S T R A C T

Although the conventional long baseline (LBL) positioning system has high positioning accuracy, it does not properly account for the motion of autonomous underwater vehicles (AUVs) and thus causes error between the time and the location of the signal sent compared to the signal received. This error affects the positioning accuracy and real-time positioning of the system. In this study, we constructed a model based on an extended Kalman filter (EKF) in an effort to resolve this problem. The model uses multiple-beacon ranging information, depth information, and velocity information as the primary observations based on which it can manage any amount of beacon distance information. The multi-beacon, EKF-based integrated navigation algorithm yielded results in close agreement with experimental data; the system error was restrained and effectively converged. After data pre-processing, the four beacon navigation systems reaches meter-level accuracy. Compared to the traditional LBL positioning system, the integrated navigation algorithm is more accurate over a wider range. It can be used to provide more stable and accurate position information for any given target in real time, making it very well-suited to AUV integrated navigation systems with multiple beacons.

1. Introduction

Autonomous underwater vehicles (AUVs) play a significant role in a wide array of civilian and military underwater applications(Tan et al. (2011),Kalyan and Balasuriya (2004)). When the AUV works underwater, its navigation system provides high-precision absolute/relative position information (Wang (2013a, b)). The position information is not only used to determine spatial locations, but also as an important safeguard for overall effective AUV application and safe recovery. The sound wave is the most effective carrier for transmitting information, making underwater acoustic positioning systems (UAPSs) essential positioning and navigation components of AUVs and remotely vechiles (ROVs)(Han et al. (2016)). The AUV, which relies on an inertial navigation-dead reckoning system, cannot perform with complete navigation accuracy due to cumulative error. It is necessary to rely on an acoustic positioning system to correct for cumulative error in the inertial navigation system when the AUV works over long periods of time in the deep sea. (Allotta et al. (2015),Matos and Cruz (2005)).

Although the conventional long baseline (LBL) positioning system has high positioning accuracy(Li et al. (2015), Baccou et al. (2001)), it ignores the influence of the underwater vehicles motion. This makes the time and location of the signal sent different from those of the signal received, which affect the vehicles positioning accuracy and capacity for real-time positioning[N H Kussat and Chadwell, 2005,Lan (2007)]. The Kalman Filter represents an effective approach to resolving this problem (Chen and Wang, 2013,Wynn et al. (2014),Sabet et al. (2014)), as it is currently a popular method for tracking target motion in many engineering applications. It can effectively integrate redundant information from a variety of external sensors to form a single observation system with enhanced performance.

B. Allotta proposed a navigation algorithm for AUVs based on an unscented Kalman filter which allows for the direct processing of highly nonlinear and nondifferentiable systems(Allotta et al. (2016a)). Detweiler C and Leonard J proposed a global acoustic beacon joint time synchronization alternative response mode which can be obtained directly by a one-way distance value(Detweiler and Leonard, 2006, Webster et al. (2010)). This method is suitable for systems that operate for brief durations. Author(s)(Li (2016)) took the residual error as the correction quantity based on the theory of ray acoustics and Bayesian inversion to establish a motion compensation algorithm. Their algorithm is suitable for systems with at least $0.1ms$ timing accuracy. Yiming Chen proposed a neat-real-time(NRT), it can address the asynchronous nature of LBL measurements as well as model nonlinearities. Because the LBL positioning cycle in Chens paper is short, it almost has not error

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between the time and the location of the signal sent compared to the signal received, so it is suitable for small AUVs in harbor environments rather than larger scope. And because the influence of water flow, the yaw error is large. Chen et al. (2016)).

In an effort to resolve the problems in LBL positioning systems, we constructed an integrated navigation model based on an extended Kalman filter (EKF). The integrated navigation model uses distance and velocity as observations based on which it updates the position information of the target when receiving the distance information of any number of beacons. The solution model can guarantee a wide-ranging and accurate navigation system. Below, we first introduce the basic principle of LBL and its shortcomings. We then propose an EKF model based on multi-beacon ranging tailored to the shortcomings of the LBL system. Two methods are then established for treating measurement data to reduce the positioning error and filtering divergence caused by outliers. We verify the feasibility of this approach by experimental data processing, then discuss the accuracy of the proposed navigation system.

2. Navigation application of LBL positioning system

The LBL positioning system has a variety of solution models, the most common of which is the spherical intersection model. The model uses distance information as the measurement data, and underwater vessel navigation problems are traditionally solved via the least square method(Cao et al. (2017)).

When the LBL is positioned for the underwater vehicles, the interrogation signal is sent periodically via a ranging unit mounted on the vehicle after receiving the response signal of all the sound beacons. The distance between the ranging unit and each sound beacon is obtained according to the two-way propagation delay and the speed of sound; the position of the acoustic beacon is then calculated according to the geographical coordinates of the acoustic beacon. However, underwater vehicles are usually in motion.

As shown in Fig. 1, when the underwater vehicle is in the signal transmission to response process, the ranging unit in the signal transmission and the reception time coordinates are different thus the underwater vehicle to sound beacon and sound beacon to underwater vehicle corresponding to the propagation time are not the same. The time and position of the different beacon response signals received are different because the distance between the target and each beacon is different. The conventional LBL positioning model does not account for the influence of the target motion, and the distance values corresponding to half of the propagation delay are taken as the observed distance information values. The location solution is obtained, then the actual coordinates of the target are obtained.

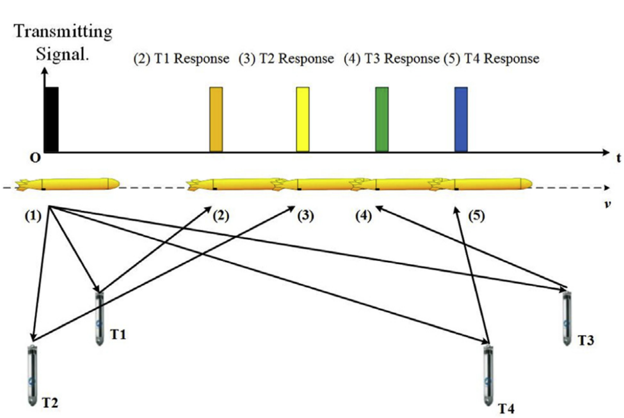

Fig. 1. Effect of the underwater vehicles motion on long baseline positioning.

Only Detweiler C, Leonard J, and Author(s) (Detweiler and Leonard, 2006) proposed a solution to the above problem. However, when working in the deep sea for any long-term period, the battery life and the coherence of the beacon clock offset affect the continuity and effectiveness of the system. The dynamic positioning error is even larger if the time measurement precision is insufficient.

In this study, we developed an EKF model based on multi-beacon ranging. The motion model is established based on the analysis of the target motion state; the moving state of the target, such as speed, heading, and attitude, is integrated with the acoustic positioning data. This reduces the influence of target motion on the positioning system is reduced. The conventional Kalman filter is the minimum mean square error estimate which applies to the target motion model and linear Gaussian case of the observed model. However, in the navigation system, the state equations and measurement equations are often nonlinear which renders conventional Kalman filtering no longer applicable.

The EKF is suitable for nonlinear weak estimation objects (Wang and Wang, 2012), and the unscented Kalman filter is suitable for nonlinear strong estimation objects (Khairnar et al. (2007)). AUVs move at uniform and low speed. AUV's acceleration is very slow and its mobility is weak. So the system motion model established with AUV is simple and the measurement information of AUV is single. For these reason, EKF can be used to meet system requirements(Allotta et al. (2016b),Modalavalasa et al. (2015)).

3. EKF model based on multi-beacon distance measurement

3.1. Introduction to EKF

For a nonlinear system, the system state equation and measurement equation are (Qin et al. (2012)):

$$X_k = f(X_{k-1}, k-1) + G_{k-1}W_{k-1}, \tag{1}$$

$$Z_k = h(X_k, k) + V_k, \tag{2}$$

where f is an n-dimensional nonlinear vector functions, h is an m-dimensional nonlinear vector function. W_k is the r-dimensional random system noise distribution sequence, and V_k is the m-dimensional measurement system noise sequence.

We can ignore higher-order terms above the first order based on Taylor expansion of the state equation and measurement equation for the nonlinear system, which allows the use the linearized equation approximation nonlinear function. This yields the following formula:

$$X_k = f(X_k, k-1)|_{\widehat{X}_k} + \frac{\partial f(X_k, k-1)}{\partial X_{k-1}^T}|_{\widehat{X}_k} \Delta X_k + G_{k-1}W_{k-1}, \tag{3}$$

$$Z_k = h(X_k, k)|_{\widehat{X}_k} + \frac{\partial h(X_k, k)}{\partial X_k^T}|_{\widehat{X}_k} \Delta X_k + V_k, \tag{4}$$

In an actual system, if the initial state quantity $\widehat{X}_0$ and initial covariance P_0 are known, the conventional Kalman Filter recursive formula allows the estimated amount $\widehat{X}_k$ of the state variable at time to be recursively determined based on the measured value Z_k at time k.

3.2. Modeling and construction of model based on EKF

AUVs and other underwater vehicles usually have highly precise measuring facilities. In our subsequent calculations, the depth of information is considered a known quantity and we only consider the target in the horizontal state of motion.

Common motion models include the CV model, CA model, Singer model, and current statistical model. Underwater vehicles are characterized by weak maneuverability of linear motion, slow acceleration,