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Intelligent assistance positioning methodology based on modified iSAM for AUV using low-cost sensors

Jia Guo, Bo He *, Huan Duan

School of Information Science and Engineering, Ocean University of China, 238 Songling Road, Qingdao 266100, China

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ABSTRACT

This paper focuses on the application of low-cost sensors for autonomous underwater vehicle (AUV). We propose an intelligent assistance positioning methodology by combining the modified incremental smoothing and mapping (iSAM) and constrained optimally pruned extreme learning machine (OP-ELM) for low-cost sensors, which makes full use of GPS data and produce a variety of correction models. Compared to relinearizing and variable reordering by period batch step in the original iSAM, modified iSAM is implemented variable reordering alone and conducted adaptive relinearization when the value of local Chi-square exceeded a certain threshold. Meanwhile, a novel constrained OP-ELM is presented by mapping the output to the constraint space, which provides full guarantee for generating reliable correction model. When GPS is valid, the constrained OP-ELM is applied to the low-cost sensors to generate correction model. Simultaneous, the correction model of measurement for modified iSAM is also given by this way. Once GPS becomes invalid, the correction models are used to amend the low-cost sensors data and measurement model for getting more accurate location information. Experimental results and analysis show that the proposed method outperforms the traditional algorithm, which RMSE can improve by at most 83.8% than Extended Kalman Filter's (EKF).

1. Introduction

Autonomous underwater vehicle (AUV) is an indispensable instrument for using in the complex underwater environment such as the ocean survey, due to its flexibility and autonomy. Although GPS is used as a significant sensor in unmanned vehicles or unmanned aerial vehicles (UAV), it is limited or even unusable for AUV. However, simultaneous localization and mapping (SLAM) (Bailey and Durrant-Whyte, 2006; Cheeseman et al., 1987; Durrant-Whyte and Bailey, 2006; Leonard et al., 1992; Thrun, 2002) can create a consistent map in real time and can acquire estimated position information simultaneously even under water. Therefore, SLAM, which can provide feasible solution for the realization of autonomous navigation, has received considerable attention for mobile robot in unknown environment (Bonin-Font et al., 2015; Chen and Guo, 2014; Lee et al., 2012; Newman and Leonard, 2003; Newman et al., 2005; Ribas et al., 2006; Wen et al., 2015).

Simultaneous localization and mapping (SLAM) also plays an important role in autonomous navigation for AUV. Extended kalman filter (EKF) (Bonnabel and Slotine, 2015; Kalman, 1960) is a classical method, because the theory of this algorithm is straightforward and easy to implement. However, the main problem of EKF is the existence of accumulated error, which is generated in linearization processing. Subsequently, to improve the drawback of EKF-SLAM, many algorithms such as particle filter (PF) (Liu and Chen, 1998) and unscented kalman filter (UKF) (Kitagawa, 1996) were proposed. These algorithms still have a certain negative effect. The increased computational complexity or the loss of computational stability are the problems which these algorithms are facing with. Furthermore, sparse extended information filters (SEIF) (Thrun et al., 2004) gets the approximation map of environment in fixed time-step, and suffers from poorly consequence when confronts with a closed-loop. Incremental smoothing and mapping (iSAM) (Kaess et al., 2008), which focuses on improving the accumulated errors, was proposed by Michael Kaess in 2008. While filtering may bring unbounded accumulated errors by marginalizing previous pose, iSAM recovers the complete trajectory and the map to avoid the problem. In non-linear system, iSAM adopt periodic variable reordering together with relinearization. iSAM 2 (Kaess et al., 2011) was proposed according this principle by using the Bayes tree to perform the process of relinearization and variable reordering in where it is needed.

However, no matter what kind of SLAM algorithm (Koch et al., 2017; Ma et al., 2016; Zhang et al., 2017), in practical SLAM applications, high-quality sensors and accurate measurement model are more

* Corresponding author.
E-mail address: bhe@ouc.edu.cn (B. He).

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beneficial to improve the navigation performance. However, the high cost of high-quality sensors impede the widely research on AUV. Furthermore, the complex process to determine the measurement model not only costs a lot of manpower and resources, but also has very poor versatility. Once the sensor in AUV is replaced or the position of sensors changes, the accurate measurement model has to readjust accordingly. It greatly delays the development time of AUV.

Compared to high-quality sensors, the low-cost sensors are cheap, but has the characteristics of low accuracy. Since the sensor data has a crucial impact on the navigation for AUV, how to deal with the data of low-cost sensors is the key process for using them by SLAM for AUV. Meanwhile, how to quickly and efficiently build the accurate measurement model are also important to the proper usage of SLAM.

Since the valid GPS signal can provide more accurate track than low-cost sensors, during the last few years, the vast majority of algorithms devote to integrate GPS and low-cost sensors using artificial neural network (ANN) (Demuth et al., 2014; Semeniuk and Noureldin, 2006; Sharaf and Noureldin, 2007; Sharaf et al., 2005), However, these algorithms are mostly applicable to vehicles and unmanned aerial vehicles. When referred to AUV, which can only receive little or no valid GPS signals, few work is reported. The classical ANN algorithms include least squares support vector machine (LS-SVM) (Ghaedi et al., 2014; Suykens et al., 2002; Yang et al., 2002), random forest regression (RFR) (Liaw and Wiener, 2002; Lindner et al., 2015), radial basis function (RBF) (Lei and Li, 2013; Sharaf and Noureldin, 2007) and so on. Usually, according to whether the GPS is effective or not, there are two different modes of operation: learning mode and prediction mode. However, the input which exceeds the range of learning mode will affect the prediction accuracy (Xu et al., 2016). In 2004, Huang (Huang et al., 2004, 2006; Wan et al., 2014) proposed extreme learning machine (ELM), which outperforms traditional algorithm not only in speed but also in generalization performance. Based on the original ELM algorithm, optimally pruned extreme learning machine (OP-ELM) is presented to make it more robust and generic (Similä and Tikka, 2005). It can be used to provide a better guarantee for the application of AUV in practice.

In this paper, we have proposed an intelligent assistance positioning methodology, which combines modified iSAM and constrained OP-ELM. We perform variable reordering alone and conduct adaptive relinearization for iSAM when the value of local Chi-square exceeds a certain threshold without operating Bayes tree. Simultaneously, a constrained OP-ELM is proposed to generate correction model for low-cost sensor data, while the accurate measurement model is also given by the constrained OP-ELM. By combining the corrected model with modified iSAM, the more accurate position of AUV will be offered.

The remainder of the paper is organized as follows. Section 2 is the overview of proposed intelligent assistance positioning methodology. The principle of the modified iSAM and the constrained OP-ELM are introduced in section 3. In section 4, experiments with different datasets will be carried out to verify the performance of the proposed algorithm. Finally, we draw the main conclusions of this work.

2. Overview of proposed intelligent assistance position methodology

Traditionally, when AUV sails on the surface of the water, GPS receiver which is located in AUV receives signal from the satellite. At this time GPS data is valid and can provide accurate position information for AUV. Although other sensors such as AHRS or DVL also keep working during this process, the position calculated by these sensors usually may not be used or may be used only when GPS outages happens, due to the low accuracy of the sensors. On the other hand, in addition to providing a more accurate initial values, GPS data has no effect to calculate underwater AUV position, which become invalid in this circumstance. So, it is significant to make a compromise between the inadequate usage of data and performance improvement of low-cost sensor. In this paper, a novel intelligent assistance positioning methodology based on modified iSAM and constrained OP-ELM for AUV is proposed to correct low-cost sensor data and get accurate measurement correction model. The whole propose intelligent assistance positioning methodology is illustrated in Fig. 1. By inputting the sensors data such as AHRS or DVL into constrained OP-ELM, we get the corresponding correction model of low-cost sensor. Then the sensor information is considered to be compensated by combining sensors data with correction model. As the direct nonlinear relationship between the output value and the true value is obtained by the correction model, the correction model in some sense is the mapping of all errors and noises on output. In other words, sensor data corrected by correction model is thought to have eliminated the interference of other factors. When the corrected data is sent into modified iSAM, the trajectory should have been equivalent close to the real track. However, there is still difference between the trajectory which is generated by modified iSAM and the real one. We suppose that the reason for this situation is caused by inprecise measurement model. Hence, similar to sensors, the measurement model is obtained by correction of constrained OP-ELM. Once

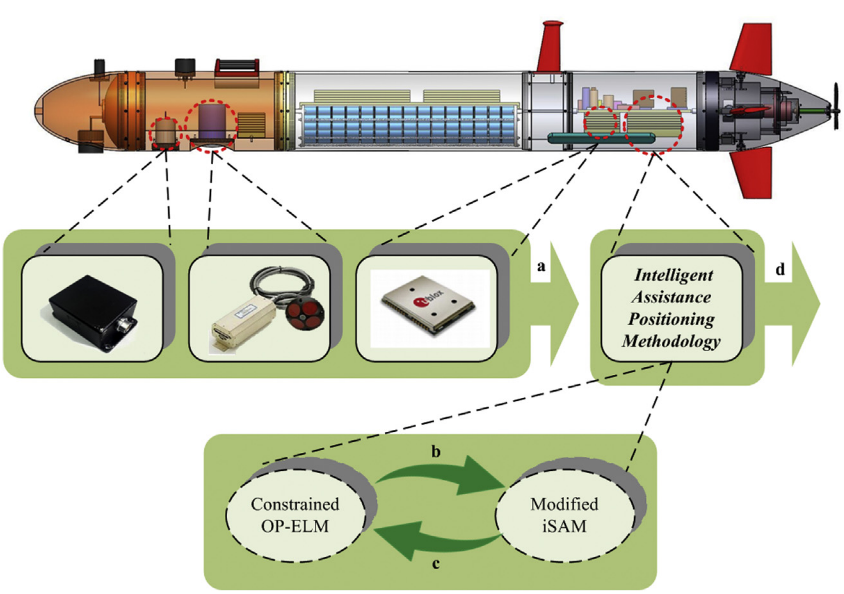

Fig. 1. The whole proposed intelligent assistance positioning methodology. Learning process includes a) send sensors data into constrained OP-ELM for generating correction model, b) send corrected data into modified iSAM to generate rough position, c) send rough position to constrained OP-ELM for generating measurement correction model. Predict process includes a) combine sensors data with correction model in constrained OP-ELM, b) send corrected data into modified iSAM to generate rough position, c) combine rough position with measurement correction model in constrained OP-ELM.