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Shallow-sea application of an intelligent fusion module for low-cost sensors in AUV

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ABSTRACT

This paper focuses on the application of AUV in shallow-sea, which environment is more complicated than deep-sea. Owing to independence of external signals, inertial navigation system (INS) has become the most suitable navigation and positioning system for underwater vehicles. However, as the excessive reliance on sensor data, the precision of INS can be affected by external environment, especially heading angles from low-cost sensors such as attitude and heading reference system (AHRS) and digital compass are susceptible to waves and magnetic interference. Therefore, how to use data from low-cost sensors becomes the key to improving navigation performance. Optimally pruned extreme learning machine (OP-ELM) was presented as a more robust and general methodology in 2010, which make it possible to fuse data by using a more reliable method. In this paper, we propose an intelligent fusion module which is designed to obtain the full-noise model for AUV. By judging the state of AHRS and TCM heading angles, intelligent fusion module combines full-noise model with credible data by using OP-ELM to improve the accuracy of positioning and navigation. Our method has been demonstrated by a range of real data, which RMSE can at most improve by 86.4% in complex conditions than Extended Kalman Filter's.

1. Introduction

Autonomous underwater vehicle (AUV) is an indispensable instrument, which is used in the complex underwater environment such as the ocean (Lee et al., 2012), due to its flexibility and autonomy. However, when AUV is in operation in shallow-sea, complex external environment such as ferromagnetic substance will have a serious effect on the direction of AUV. In addition, the strong ocean currents also have certain influences on navigation. Therefore, it is meaningful to overcome unfavorable factors in shallow-sea to achieve high-precision navigation for AUV.

Although GPS is used as a significant sensor in unmanned vehicles or unmanned aerial vehicles (UAVs), it is limited or even unusable for AUV. However, simultaneous localization and mapping (SLAM) (Cheeseman et al., 1987; Leonard et al., 1992; Thrun, 2002) can create a consistent map in real time and acquire estimated positioning information simultaneously even under water. Therefore, SLAM has received considerable attention for underwater vehicles in unknown environment (Newman and Leonard, 2003; Newman et al., 2005; Ribas et al., 2006), which can provide feasible solution for the realization of autonomous navigation.

Traditionally, there are lots of sensors installed in AUV, including AHRS, digital compass, pressure sensor, GPS and doppler velocity log (DVL), which are mainly used for navigation and positioning. Most of them are used more frequently in motor vehicles and UAVs. However, due to the low precision, the merely usage of low-cost sensors cannot provide satisfactory navigation performance for AUV. We take AHRS and digital compass as example. AHRS contains a plurality of axial sensor, which can provide heading, pitch and roll angles for AUV. However, surge, acceleration, deceleration and even other factors will inevitably bring angle errors. Once the angles, especially heading angles, are not accurate, navigation performance of AUV would not be guaranteed. Even though most of AHRS can be input external global navigation satellite system (GNSS) signal to correct angle errors during the process of movement. Nevertheless, GPS is invalid in water so that the compensation of angle errors cannot be achieved. And when it comes to digital compass, it is vulnerable to interference of ferromagnetic substance. Thus, merely using low-cost sensors data cannot meet the demand for navigation of AUV. Therefore, many algorithms have been proposed to improve the performance of AHRS and digital compass. The main method is dynamic compensation (Blank et al., 1997; Qiang et al., 2009; Schierbeek et al., 2003; Smith et al., 2003;

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Včelák et al., 2006; Wang et al., 2014). There is no doubt that these methods have played a role in improving the angle accuracy of digital compass or AHRS. However, no matter temperature variation, change of magnetic field or other factors, the vast majority of methods only focus on only one factor, ignoring the effects of other factors. For example, Robert B. Smith et al. (2003) proposed a three-axis algebraic model which is used to numerically compensate for magnetic errors by only measuring magnetic field values. Similarity, a temperature compensation method was presented by Qiang Fu for the MEMS accelerometer in the AHRS (Qiang et al., 2009).

Different from these improved methods, we propose an intelligent fusion module which focuses on seeking out the full-noise model instead of compensating for low-cost sensors. The intelligent fusion module not only takes sensors' error into account, but also external environment. OP-ELM (Miche et al., 2008a, 2010, 2008b) is presented by Miche Y et al. Compared with Support Vector Machine (SVM) (Gunn, 1998; Smola and Vapnik, 1997; Yang et al., 2002) and ELM (Huang et al., 2012, 2004, 2006), OP-ELM has been demonstrated to be more suitable to generate the intelligent fusion module for AUV in this paper. In this paper, we take heading angles which are from digital compass or AHRS for example. Because some circumstance such as strong magnetic or violent acceleration/deceleration may cause untrustworthy data for sensors, we judge status of sensors' data and adopt different full-noise models which are obtained by OP-ELM for credible sensors’ data in the intelligent fusion module.

The paper is organized as follows: Section 2 is the full-noise model using OP-ELM. The intelligent fusion module for AHRS and digital compass will be presented in Section 3. In section 4, the result of experiments with different datasets have verified the performance of the proposed algorithm. Finally, we draw a conclusion of this work.

2. The full-noise model using OP-ELM

2.1. Traditional correction and the proposed full-noise model for low-cost sensors

Current ways for the improvement of navigation performance for AUV, which use low-cost sensors, are the compensation method. Traditional corrections of digital compass mainly include system error compensation, soft magnetic compensation and hard magnetic compensation. The system error usually comes from manufacture error and installation error of sensors. In general, system error is inherent in the digital compass and does not change with external factors. Wei Chen proposed an easy-to-use and computation-efficient correction, utilizing the heading angles from GPS to estimate the parameters of this model in the procedure (Miche et al., 2010). J. Včelák focused on seeking methods to compensate error caused by sensors misalignment, cross-axis effect and drifts of temperature for sensors (Včelák et al., 2006). Although different methods were used to perform compass compensation, the general principle of these methods is to get the parameters of compensation by executing many complex experiments, following with one-time compensation for compass. Hard magnetic interference are generated by Magnetic dipole, and it will cause a deviation to output of digital compass. However, for the compass, the toughest thing is to deal with soft magnetic interference. Soft magnetic interference is caused by the distortion of the local magnetic field. In the case of soft magnetic interference, the measured curve will be an ellipse. For these magnetic interference in the environment, it is necessary to determine its spatial relationship with sensor to compensate the error of compass. Nevertheless, AUV, which need to go to explore the unknown area, is impossible to obtain the exact location of the magnetic interference substance. For AHRS, it has the problem of accumulated angle error. What's more, acceleration/deceleration is inevitable in AUV operation. And the usage of GNSS signal to correct the angles in underwater is invalid for AHRS. Therefore, we need to make reasonable use of low-cost sensors data to improve navigation performance.

Different from the traditional angle correction, the proposed method aims to improve the navigation performance by using data from low-cost sensors directly, rather than only consider the compensation of these low-cost sensors. As we mainly focus on large-scale marine investigation and detection, therefore, the sway of AUV in local area is avoided as much as possible. Assuming that TCM/AHRS is not affected by external environment and the accuracy of them is high enough, the heading angles of TCM/AHRS will be consistent with course heading angles from GPS. In fact, the factor of external interference and sensor errors are unavoidable. So, only considering one factor, it is difficult to achieve high-precision navigation. On the basis of these problems, we adopt neural network to generate the full-noise model, which describe the relationship between the sensors heading angles and course heading angles which comes from GPS. The course heading angles which are obtained from GPS rather than the vehicle heading angles are treated as the truth heading angles for training the full-noise model, because the course heading angles from GPS are the resultant heading angles which are generated by vehicle heading angles and all the other influencing factors on heading angles, such as magnetic interference and water current. This is why GPS heading angles rather than vehicle heading angles are selected as the truth heading angles both in the module and in the following comparison.

As the certain number of samples can not cover the full range of inputs, the generalization ability and prediction accuracy of the most types of neural network can not be guaranteed. However, extreme learning machine (ELM) have been proved that it can outperform other conventional neural network in above circumstance (Xu et al., 2016). ELM was proposed by Huang et al. and the main novelty introduced by ELM is to randomly choose the input weights and biases of the hidden nodes instead of learning these parameters. OP-ELM was presented as a more robust methodology, which is based on the original ELM algorithm. It is verified and demonstrated in the following part that the performance of OP-ELM exceeds other neural network such as SVM and ELM. The specific calculation method of full-noise model which uses OP-ELM is in Section 2.2.

2.2. Review of OP-ELM

The full-noise model is treated as signal-hidden layer feed-forward neural networks (SLFNs). The output of SLFNs with N hidden nodes can be presented as:

$$f_n(x) = \sum_{i=1}^{n} \beta_i G(\omega_i, b_i, x) \qquad x \in R^n, \omega_i \in R^n, \beta \in R^n. \tag{1}$$

where $G(\omega_i, b_i, x)$ is the ith output of hidden-layer neurons corresponding to the input. $\beta = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{im}]^T$ represents the connecting link between the ith hidden-layer neurons and weight vector of output neurons.

For N arbitrary input sample, where $x_i = [x_{i1}, x_{i2}, \cdots, x_{in}] \in R^n$ and $t_i = [t_{i1}, t_{i2}, \cdots, t_{in}] \in R^n$, given N hidden-layer neurons and activation function $G(\omega_i, b_i, x)$, β_i, ω_i and b_i can be found out to make SLFNs close to the N samples with zero error.

$$\sum_{j=1}^{n} \beta_j G\left(\omega_j, b_j, x_i\right) = t_i \qquad i = 1, 2, \cdots, N. \tag{2}$$