AUV Dead-Reckoning Navigation Based On Neural Network Using a Single Accelerometer

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ABSTRACT—the accuracy of the Autonomous Underwater Vehicles (AUVs) navigation system determines whether they can safely operate and return. Traditional Dead-reckoning (DR) relies on the inertial sensors such as gyroscope and accelerometer. A major challenge for DR navigation is from measurement error of the inertial sensors (gyroscope, accelerometer, etc.), especially when the AUV is near or at the ocean surface. The AUV's motion is affected by ocean waves, and its pitch angle changes rapidly with the waves. This rapid change and the measurement errors will cause great noise to the direction measured by gyrosopes, and then lead to a large error to the DR navigation. To address this problem, a novel DR method based on neural network (DR-N) is proposed to explore the time-varying relationship between acceleration measurement and orientation measurement, which leverages acoustic localization and neural network estimate timely pitch angle through the explored time-varying relationship. This method enables AUV’s DR navigation with a single acceleration, without relying on both acceleration and gyroscope. Most importantly, we can improve the accuracy of AUV navigation through avoiding DR errors caused by gyroscope noise at the sea surface. Simulations show DR-N significantly improves navigation accuracy.

Keywords
Dead-reckoning; Neural networks; Accelerometer

1. INTRODUCTION

AUV is becoming an important way to explore the ocean power resource due to its flexibility and the talent of long-hours' work underwater. High-precision navigation technology plays an important role in determining whether an AUV can complete its tasks. Currently, the commonly used ways of navigation are Dead-Reckoning (DR), Acoustic navigation, Geophysical navigation,

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GPS, etc. Acoustic navigation methods (LBL, SBL, USBL) uses sonar array to estimate the range and bearing to the vehicle. However, the disadvantage of this method lies in its limited distance, and the deployment and recovery of acoustic arrays increase the complexity. For geophysical navigation, the cost of transcendental environment mapping diagram is high and the match work is very difficult. And the GPS system's radio signals will be absorbed by sea water, thus GPS signals cannot be directly received by deeply submerged ocean vehicles. DR is a low cost method of navigation with simple implementation. DR requires inertial sensors, usually a gyrocompass and an accelerometer, to estimate the orientation and distance traveled by the tracked object with respect to a reference coordinate system. The key challenge of DR is the measurement error of its inertial sensors (gyroscopes), especially when AUV sails near or at the surface of the ocean, the pitch angle of AUV is fast time-varying, which causes big measurement noises from gyroscope and eventually affect navigation. Besides, a high precision gyroscope is very expensive, and its volume is too large to be installed in all kinds of AUVs [1]-[4].

In this paper, we proposed an approach named DR-N, which is based on the DR navigation and BP Neural network. It explores the time-varying relationship between the acceleration and the pitch angle of AUV, and then obtains the pitch angle by using the measurement of the acceleration and the explored relationship. With this method, we can obviate the need of calculating the AUV time-varying pitch angle via direct measurement of gyrocompass, and track the AUV with only a 3-D accelerometer.

The remainder of this paper is organized as follows. The description of DR-N method is introduced in Section 2. Section 3 shows the performance of our algorithm in simulations. Finally, conclusions and future work are shown in Section 4.

2. DESCRIPTION of DR-N

In this paper, we do not intend to use the measurement of gyroscope to calculate the pitch angle. Instead, we propose a novel approach which only uses a single 3-D acceleration sensor with the help of BP Neural network.

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Our method, denoted as the DR-navigation-based-on-the-neural-network (DR-N), applies a 3-D acceleration sensor and a depth sensor, and divides the navigation procedure into two kinds of time periods as learning-time-period (LTP) and prediction-time-period (PTP). A flow chart of DR-N is given in Figure 1.

**2.1 Estimation of The Pitch Angle**

In order to estimate the pitch angle of AUV, we need to locate the AUV every L seconds during LTP through acoustic localization or any other methods of localization, the estimated positions represented as \( L(x_i, y_i), k = 1, 2, ..., Q \), we only need to locate a few times, so we combine multiple technology to ensure the accuracy. As shown in Figure 2 the time between \( L_0 \) and \( L_1 \) is L seconds, the coordinates of which are \( (x_{0i}, y_{0i}) \) and \( (x_{1i}, y_{1i}) \), we divide this period into \( N_L \) slot, so \( N_L = \frac{L}{H} \), note that the time slot H is very short, so we suppose that the AUV’s pitch angle is constant during every slot. In the \( n^{th} \) time slot, at time \( t_n, n = 1, ..., N_L \), the accelerometer device produces three-axis acceleration measurement vector, \( \dot{a}_n = [\dot{a}_{nx}, \dot{a}_{ny}, \dot{a}_{nz}]^{\top} \), at local coordinates, which are grouped into a matrix \( \dot{A}_n \), and the depth sensor produces the depth measurement \( h_n, n = 1, ..., N_L \). Then we can estimate the pitch angle with these data, the details are as follows:

**Algorithm A: Pitch Angle Estimation**

**Step1**: Calculate the distance between \( L_0 \) and \( L_1 \) as 
\[
\text{target} = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}
\]
and divide it into \( N_L \) sections on average, we set \( d = \frac{\text{target}}{N_L} \), \( S_k = [s_{ki}, s_{kj}] \), \( s_i = d \), \( i = 1, 2, ..., N_L \) initially.

**Step2**: Calculate the pitch angle every \( H \) seconds, 
\[
\rho_i = \arctan \left( \frac{h_{ki} - h_{kj}}{s_i} \right), i = 1, 2, ..., N_L.
\]

**Step3**: Predict the position of \( L_1 \) from start point \( L_0 \) by using the three-axis acceleration measurement \( \dot{a}_n \), and converge the coordinate system first, \( \alpha_i = \text{Tr}(\alpha_i) \odot \dot{a}_n, i = 1, 2, ..., N_L \), \( \text{Tr}(\alpha_i) \) represents the transform matrix. We assume that the AUV moves with constant acceleration every \( H \) second, so
\[
\ddot{s}_i = \dot{s}_i + \frac{1}{2} \left( v_{ix} \times \Delta t + \frac{1}{2} \times a_{nx} \times \Delta t^2 \right) + \frac{1}{2} \left( v_{iy} \times \Delta t + \frac{1}{2} \times a_{ny} \times \Delta t^2 \right),
\]
i = 1, 2, ..., \( N_L \) and in which \( \dot{s}_i = 0 \), \( v_{ix} = v_{ix} + a_{nx} \times \Delta t \), \( v_{iy} = v_{iy} + a_{ny} \times \Delta t \), \( \dot{s}_i = \rho_i \), \( \ddot{s}_i \) is the prediction about the \( L_1 \), and we set \( S_k = [s_{ki}, s_{kj}] \).

**Step4**: Set \( e = \text{target} - \ddot{s}_i \), \( e \) represents the error between the predict position and true position of \( L_1 \). Then divide the error \( e \) into \( \ddot{s}_i \) equally, \( i = 1, 2, ..., N_L \), to update position of every \( H \) seconds, that is to say set \( S_k = S_k + \frac{e}{N_L} \), and update the value of \( S_k \) as \( S_k = S_k \).

**Step5**: Back to the Step2 and continue the cycle Step2 → Step5 until it converges.

**Step6**: The method is convergent when the error \( e \rightarrow 0 \), or the difference of two consecutive value of error \( (e_{i+1} - e_i) \) → 0 . After the convergence, we can get the estimation of pitch angle.
model between them with the training data. The input layer has three nodes, which are the three-axes accelerometer measurements \(a_{x}, a_{y}, a_{z}\), and the output layer has one output node \(\rho_{o}\), representing the corresponding pitch angle. We use a three-layer neural network, after large numbers of experiments, five hidden layer nodes are able to show have a good result. The activation function between the input layer and the hidden layer is the logsig function, and the activation function between the hidden layer and the output layer is the tansig function. The training method used is the adaptive learning rate gradient descent method. Second, after the training process, we use the net1 to get the predict value, and then calculate the error between the true value and predict one, represented as \(\text{error} = \rho_{o} - \rho'_{o}\). Then the error is added to the input layer, so that the input layer has four nodes, which are the three-axis accelerometer measurements \(a_{x}, a_{y}, a_{z}\) and the error. However, the other settings of the net don’t need to change. Then with this new data, we perform the training process for the second time to get the net2. So the net1 and net2 compose the learning process of this algorithm, and after large numbers of experiments, this structure of network with error feedback makes a great performance for our application scenarios.

as shown in Figure 4. We have some hypothesis as follows, the initial coordinate of the AUV is \((x_{0}, y_{0})\), the initial heading angle is \(\alpha_{0}\), and the pitch angle is \(\rho_{0}\). Thus, the projection of the initial speed in the horizontal plane is \(v \times \cos \rho_{0}\), and then we can calculate the coordinate of the AUV at the next moment, the calculation is as follows:

\[
\begin{align*}
x_{i} &= x_{i} + v \times \cos \rho_{i} \times \sin \alpha_{i} \times \Delta t \\
y_{i} &= y_{i} + v \times \cos \rho_{i} \times \cos \alpha_{i} \times \Delta t
\end{align*}
\] (1)

More generally, after obtaining the three-axes linear acceleration of the reference coordinate system, the coordinates of AUV at every moment can be calculated by integration. Note that it is a Two-dimensional coordinate, and the depth of AUV can be measured by the depth sensor to make it 3D.

3. SIMULATION and CASE STUDY

During simulation, a wave model is used to simulate the current of sea water. Suppose that the AUV starts from the origin of the reference coordinate system, and moves along the surface of the wave in a given scene.

3.1 The Wave Model

In our simulations we use the analytical wave model offered in [6]. Note that similar results are obtained also for other wave models. It’s the function of the height of wave, the position and the time. For the \(i^{th}\) wave frequency and \(j^{th}\) directional angle, we have the spreading directional angle, wave frequency, and an initial phase angle, respectively. The wave height is modeled as:

\[
h(x, y, t) = \sum_{i} \sum_{j} \left(2S(\varphi) \Delta \varphi \Delta \theta \cos(c_{i} \times \cos \theta_{j} + c_{y} \sin \theta_{j} - \varphi_{j} - \psi_{x,j})\right)
\] (2)

where \(h(x, y, t)\) is the height of the wave at \(t\) and in the position \((x, y)\), \(c_{i} = \frac{g}{\varphi} \) is the wave number, \(\varphi_{j}\) and \(\theta_{j}\) are the increments of angles \(\varphi\) and \(\theta\), respectively, and we use the directional spectrum function \(S(\varphi) = \frac{h_{0}^{2}}{\varphi} \exp\left[-b_{h}\left(\frac{c_{i}}{U_{\varphi}}\right)^{4}\right]\) with \(b_{h} = 8.1 \times 10^{-3}\), \(b_{h} = 0.74\), and a wind speed \(U_{\varphi} = 5\) knots. For each channel realization, parameters \(\varphi_{0}\), \(\theta_{0}\) and \(\psi_{x,j}\) are uniformly randomized in intervals \([1,5]\) rad/sec, and \(\Delta \theta = \frac{\pi}{S}\) rad [9]. An example for \(h(x, y, t)\) for \(t = 10\) sec is shown in Figure 5.

Figure 3. The Structure of Network with Error Feedback

2.3 Dead-Reckoning

After building the neural network and the training process, the future navigation is assisted with the track calculation. During PTP, the acceleration measurements is used to calculate the corresponding pitch angle by the neural network, and then using the dead reckoning method to calculate the tracks of the AUV. For easy understanding and without the loss of generality, we present the motion of AUV in two-dimensional coordinate system,
3.2 The Generation of Data and Simulation Result

In the simulation, we use the wave model to generate data, assuming that the AUV starts from the origin of the reference coordinate system and sails along the surface of the sea. Suppose that the acceleration of AUV’s forward direction \( a_x \) is fixed every 0.01 second, that means the motion of AUV is evenly accelerated during every 0.01 second, then we simulate the movement of the AUV by setting the value of \( a_{nx} \), concretely, during [1-3]s, the AUV do the uniformly accelerated motion with \( \dot{a}_{nx} = 2m/s^2 \), during [4-6]s, \( \dot{a}_{nx} = 0m/s^2 \), during [7-9]s , \( \dot{a}_{nx} = 1.5m/s^2 \), during [10-12]s \( \dot{a}_{nx} = -1m/s^2 \), and during [13-15]s \( \dot{a}_{nx} = 0m/s^2 \). After the first 15 seconds, the vector of acceleration along the AUV’s local x-axis \( \dot{a}_x \) is generated as zero-mean Gaussian process with standard deviation of 1m/sec^2, continue to 1500 seconds. We set the LTP is during [0-150] seconds, and PTP is during [150-1500] seconds.

For the calculation of the pitch angle of AUV at time \( t \) , we need to know the function of the wave at time \( t \) , the heading angle \( \alpha \) and also need to know the coordinate of AUV at this time. Suppose that, at time \( t \), the coordinate of AUV is \( A(x,y,z) \) , and the function is \( h(x,y) \) , it is easily to see that \( z = h(x,y) \). The tangent of the pitch angle is the gradient of the wave function along the heading angle at this time, the formula is as follows,

\[
\tan \rho = \frac{\frac{\partial h}{\partial x} \cos \alpha + \frac{\partial h}{\partial y} \sin \alpha}{\frac{\partial h}{\partial y} \cos \alpha - \frac{\partial h}{\partial x} \sin \alpha}
\]

then we can easily calculate the pitch angle \( \rho \). In the other hand, for the calculation of the three-axis acceleration at time \( t \), we need to know that the theoretical value of the acceleration is the sum of the three-axis linear acceleration and the three-axis’ component of gravitational acceleration at this times, shown as (4)

\[
\begin{align*}
\dot{a}_x &= \dot{a}_a + \dot{a}_g \\
\dot{a}_y &= \dot{a}_a + \dot{a}_g \\
\dot{a}_z &= \dot{a}_a + \dot{a}_g
\end{align*}
\]

3.2.1 Result of Algorithm A

In our simulation, suppose the AUV’s heading direction is fixed, so \( \dot{a}_a = 0 \), the value of \( \dot{a}_a \) is set by us, \( \dot{a}_a \) can be calculated from the change of height. On the other hand, we can calculate the component of gravity in the three axis through the pitch angle calculated by (3). So we can get the vector of acceleration through (4) to simulate the measurements of accelerometer. With AUV sails along the wave model, we can get the coordinates of AUV at any time, and we can calculate the depth of AUV measured by the depth sensor. Concretely, we set \( L=10s \) and \( H=0.1s \), so \( Q=15 \), \( N_t=100 \). Then we can estimate the pitch angle \( \rho_n \) of every 0.1 seconds during LTP by using the algorithm A, the LTP lasts for 150 seconds, so we use algorithm A for 15 times to estimate the pitch angle, the results are shown in Figure 6.

We perform algorithm A every 10 seconds for 15 times, and randomly selected 2 time periods to show the result. Figure a, b represents the comparison of predicted pitch angle \( \dot{\rho}_n \) by algorithm A and the true value of \( \rho_n \) during [0-10]s and [80-90]s respectively, in which the abscissa represents time, the ordinate represents the pitch angle, and the blue line represents the predicted pitch angle by algorithm A, the red line represents the true one. We can see the predicted value and the true value are very similar, algorithm A has a great performance, so we can use the predicted pitch angle \( \dot{\rho}_n \) to train the neural network instead of the real pitch angle approximately.

3.2.2 Train Result of Neural Network

After get the pitch angle \( \dot{\rho}_n \) and the collection of acceleration, we are able to train the network. Before the training, we add some Gaussian noise to acceleration to simulate the measurement errors. Concretely, we set \( a_n = a_r + \sigma_n \) where \( \sigma_n \) is a zero-mean Gaussian noise with variance 0.5. During LTP, there are 1500 groups of data, and we choose 1000 groups of data as learn data and use these data to train the neural network by the Gradient descent method to get the network model. and choose the rest 500 groups of data as test data, the result is shown in Figure 7, wherein the red line represents the true value of pitch angle \( \rho_n \), the blue line represents predicted value \( \dot{\rho}_n \) by algorithm A and the green line represents the predicted value \( \dot{\rho}_n \) calculated by the neural network.
The simulation result shows that the value of $\rho'_n$ is close to the actual pitch angle $\rho_n$, which proves the accuracy of this scheme. And we can track the AUV during LTP by using $\rho'_n$.

![Figure 6. Comparison of $\rho_n$, $\rho_n'$, and $\rho_n''$.](image)

**3.2.3 Result of DR-N**

After the prediction of the pitch angle, we can predict the position of AUV at any time, so we also use $S_{err}$ to present the accuracy of the proposed algorithm, whose function is as $S_{err} = \sqrt{(x-x')^2 + (y-y')^2}$, wherein the coordinate $(x, y)$ represents the actual position and $(x', y')$ represents the predicted position. $S_{err}$ represents the error between the actual position and the predicted position. As shown in Figure 8, we tracked the AUV during PTP, and selected the results of [0-1000] second to show. From the figure, we can see the error is very small, and the max error is about 4.5m at 1000s, in other words, the error is only 4.5m when the AUV sails for 1000s, so we can see our algorithm DR-N has a good result. However, we can also see the shortcoming of DR, that is the error is accumulated over time.

![Figure 7. The Error of AUV’s Position](image)

**4. CONCLUSION AND FUTURE WORK**

In this paper, for DR navigation of a AUV whose motion is affected by the ocean waves, we described a method to estimate the pitch angle and the distance traveled by the AUV using only a single 3-D accelerometer. This is required when the measurement of the AUV’s pitch angle using gyrocompass, is not available or is too noisy because of the wave near or at the surface. We propose a method using a neural network to estimate the pitch angle of the AUV and then estimate the distance traveled by it. The results of simulation show that our algorithm has a good performance.

In the experiment we also found that with the change of time error will be accumulated, in the future research we intend to combine the acoustic navigation or GPS to our algorithm to correct the position, so that the dead reckoning is more accurate. And in the future work we will do the experiment with real data collected by the AUVs.

**5. REFERENCES**

[1] A. Kose, A. Cereatti, and U. Croce, “Estimation of traversed distance in level walking using a single inertial measurement unit attached to the waist,” in IEEE Conference for Engineering in Medicine and Biology Society (EMBS), Boston, USA, Sep. 2011, pp. 1125–1128.

[2] C. Fischer and H. Gellersen, “Location and navigation support for emergency responders: A survey,” in IEEE Pervasive Computing, vol. 9, no. 1, pp. 38–47, mar 2010.

[3] F. Arrichiello, H. Heidarsson, and G. Sukhatme, “Opportunistic localization of underwater robots using drifters and boats,” in IEEE Conference on Robotics and Automation, Saint Paul, USA, May 2012.

[4] H. Tan, R. Diamant, W. Seah, and M. Waldmeyer, “A survey of techniques and challenges in underwater localization,” in Ocean Engineering, vol. 38, pp. 1663–1676, Oct. 2011.

[5] FENG Zi-long, LIU Jian, LIU Kai-zhou. “Dead Reckoning Method for Autonomous Navigation of Autonomous Underwater Vehicles,” in ROBOT, 2005, 27(2):168-172.

[6] JIAO Li-Cheng, Yang Shu-Yuan, LIU Fang, et al. “Seventy Years beyond Neural Networks: Retrospect and Prospect,” in Chinese Journal of Computers, 2016 (39).

[7] DENG Wan-Yu, ZHENG Qing-Hua, CHEN Lin, et al. “Research on Extreme Learning of Neural Networks,” in Chinese Journal of Computers, 2010, 33(2):279-287.

[8] Q. Guo, Z. Xu, and Y. Sun, “Three-dimensional ocean wave simulation based on directional spectrum,” in Applied Mechanics and Materials, vol. 94-96, pp. 2074–2079, sep 2011.

[9] Roee Diamant, Yunye Jin. “A Machine Learning Approach for Dead-Reckoning Navigation at Sea Using a Single Accelerometer,” in IEEE Journal of Oceanic Engineering, Oct 2014, :672-684