Localization of Underwater Gliders with Acoustic Travel-Time in an Observation Network

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***Abstract*—This paper presents a method to localize underwater gliders in observation networks, and this method is also applicable to other vehicles. Utilizing the travel time of acoustic signals from near-surface acoustic sources, the dead-reckoning positions of underwater gliders can be refined. Specifically, compare two kinds of travel time, one is simulated by an acoustic model for a series of possible positions of underwater gliders, and the other is the measured travel time for real positions of underwater gliders, then the most possible positions of gliders can be estimated, also the speed of ocean currents. The method formulation is based on particle filters, which could improve performance of the positioning system over time. Simulation is conducted according to experimental environment in the South China Sea, and the positioning results are compared with the dead-reckoning positions derived from experimental data, validating the effectiveness of this method.**

I. INTRODUCTION

There can be multiple vehicles in an observation network, containing floats, ships, subsurface robot swarms and etc., which need to cooperate with each other to accomplish some surveying missions. In order to conduct more effectively, that is minimizing a certain costs, such as time or energy cost, the vehicles should do path planning and strategy analyzing [1], and the primary step for the coordination of vehicles is to acquire knowledge of the surveying positions.

Underwater gliders [2], as a new type of underwater robots which combines buoy technique with Autonomous Underwater Vehicles (AUVs), are widely used in ocean observation networks, and the vast majority are assigned to conduct observation mission for the distribution of temperature, salinity and some other physical parameters [3]. Because these parameters generally have continuous distribution, the requirement for localization accuracy of gliders is low. The commonly used method is based on dead reckoning. A new hot is to take advantage of underwater gliders equipped with hydrophones to detect marine acoustic characteristics [4]. According to the prior knowledge of marine acoustic fields, characteristic distribution is complex and nonuniform [5], which makes demands on the positioning precision of underwater gliders.

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Based on the acoustic arrivals received by gliders, various processing methods can be adopted to achieve the localization of gliders. In analogy to electromagnetic waves, acoustic signals are regarded to propagate along straight lines, so positioning systems similar to Global Positioning System (GPS), like the Long Baseline (LBL) acoustic positioning system [6], can be used to estimate the positions of gliders [7]. Considering the multipath effect of acoustic signal propagating underwater, the actual propagation paths are rarely straight lines. In [8], travel-time offsets between received arrivals in the PhilSea10 Experiment and acoustic predictions predicted by a geometric acoustic ray model, are used to estimate subsurface positions of gliders using the source-receiver geometry, and when converting the travel-time offsets to range uncertainties, a uniform velocity is assumed. These methods are used to estimate the positions of gliders at a certain time under the assumption that gliders remains stationary. While in reality, gliders move continuously in the underwater environment. Combined with the motion properties of gliders, dynamic positions of gliders can be estimated. Various filters are able to achieve the estimation, such as the extended Kalman filter (EKF) [7], the unscented Kalman filter (UKF) [9], particle filter (PF) [10] and etc.

This paper formulates a method to dynamically estimate the positions of underwater gliders based on the particle filter. According to the propagation characteristics of underwater acoustic signals, the travel time is set as the measurement parameter. Through travel-time comparison between the arrivals received by gliders and acoustic predictions predicted by a Gaussian beam acoustic propagation model, the most possible positions of gliders can be estimated. The outline is as follows. In Section II, the specific problem that needs to be solved is formulated. The whole positioning system is presented in Section III, integrating the acoustic propagation model into particle filtering method. In Section IV, the simulation results of this method are analyzed.

II. PROBLEM STATEMENT

Underwater gliders are buoyancy-driven vehicles, moving up and down in the ocean without propeller system. So gliders tend to be affected by ocean currents when gliding through water columns, which results in the drifting of moving paths.

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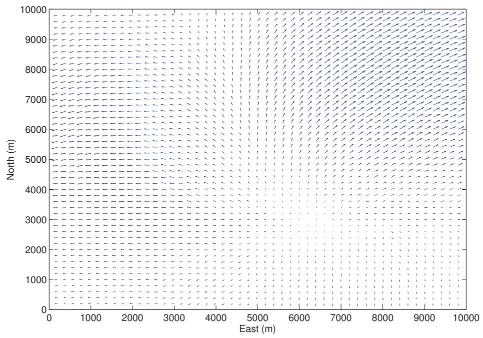


Fig. 1. Simulated ocean currents generated by ocean currents model.

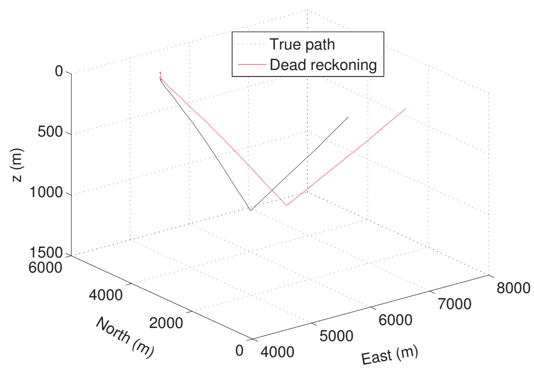


Fig. 2. One gliding profile of gliders: the red line denotes the dead-reckoning results calculated from experiment data in the South China Sea, and the black line denotes the real positions of glider under the effect of simulated ocean currents.

The ocean currents are given according to an ocean currents model in order to explain the influence of currents on glider moving, shown in Fig. 1. Processing a piece of experiment data in the South China Sea, the dead-reckoning results are calculated and the real positions of gliders are calculated under the effect of the simulated currents, as shown in Fig. 2. Although the depth of gliders can be measured by CTD, the positions of gliders still obviously drift due to the horizontal currents, which means localization only depending on the dead-reckoning method may generate big errors.

In this paper, a novel method is adopted to modify the dead-reckoning results of gliders utilizing the acoustic travel-time of signals emitted by near-surface acoustic sources.

III. Localization Algorithm

Under the consideration that acoustic signals propagate underwater is not along straight lines, travel-time of signals is set as the only measurement parameter which is the nonlinear function of spatial positions due to the nonuniform water column and the bottom and surface boundaries. A common method to calculate the travel-time of acoustic signals is to use a numerical simulation model. By comparing the acoustic travel-time corresponding to the predicted positions with the travel-time corresponding to the real positions, the most possible positions of gliders can be estimated.

The dead-reckoning method is used to predict the positions of gliders. The particle filter, an alternative nonparametric implementation of the Bayes filter [11], is applied to achieve the dynamical localization of underwater gliders. Based on the estimated results of gliders' positions, the speed of ocean currents can also be calculated iteratively.

A. Motion Model

The dead reckoning algorithm can estimate the positions of underwater gliders based on speed and heading angles which are derived from measurements from two onboard sensors, namely the pressure and electronic compass [12]. Because of the effect of ocean currents, positioning errors can accumulate over time, especially when the currents are strong. On account of this limitation, the velocity of the currents need to be estimated.

Since the depth of a glider can be measured, the positioning problem of the glider can be projected to the horizontal plane. The state of the glider at time t is denoted by $\boldsymbol{X}_t$, including the East and North components of the glider's positions in the planar coordinate system. The velocity of the horizontal current at time t is denoted by $\boldsymbol{V}_t$, also including the East and North components. So the state vector of the dynamic positioning system at time t can be represented by $\{\boldsymbol{X}_t, \boldsymbol{V}_t\}$, and the state vector can be modeled as

$$\boldsymbol{X}_t = \boldsymbol{X}_0 + \int_0^t (\boldsymbol{V}_t^g + \boldsymbol{V}_t)dt, \tag{1}$$

where $\boldsymbol{X}_0$ is the initial state and $\boldsymbol{V}_t^g$ is the horizontal velocity of the glider relative to the current at time t, which can be calculated by the dead reckoning algorithm under the assumption that the vertical velocity of the current is zero.

Assume that the horizontal velocities of both the current and the glider relative to the current are constants within the time step from time $t-1$ to time t, the dynamic evolution of the state can be provided by

$$\boldsymbol{X}_t = \boldsymbol{X}_{t-1} + (\boldsymbol{V}_t^g + \boldsymbol{V}_{t-1})\Delta t. \tag{2}$$

Here, $\boldsymbol{V}_t^g$ is the real value derived from post processing of the glider's measurements, and $\boldsymbol{V}_{t-1}$ is the estimated value calculated from the previous time step by

$$\boldsymbol{V}_{t-1} = \frac{\boldsymbol{X}_{t-1} - \boldsymbol{X}_{t-2}}{\Delta t} - \boldsymbol{V}_{t-1}^g. \tag{3}$$

B. Acoustic Measurement Equation

For the predicted positions of underwater gliders, external measurements acquired by hydrophones equipped on gliders are used to modify the predictions. Here, the travel time is selected as the measurement which is related to positions of the glider. The measurement equation is defined as

$$T_t = h(\boldsymbol{X}_t, env) + e_t, \tag{4}$$

where T_t is the measurement of acoustic travel time at time t, $h(\boldsymbol{X}_t, env)$ is the travel-time function depending on both the positions of the glider and the environment of traveling, and e_t is the measurement noise. Generally, the parameter env is a function of the sound speed profile of the environment and the sea-surface and bottom boundaries.

Only in exceptional cases, exact solutions of $h(\boldsymbol{X}_t, env)$ can be found [5]. The Gaussian beam acoustic propagation model BELLHOP [13] is used to calculate the acoustic travel time corresponding to $\boldsymbol{X}_t$, given input information: positions of acoustic sources and environmental parameters.

C. Particle Filter Implementation

The particle filter is used to estimate the most possible positions of the glider on the basis of the reconstructed probability distribution of the state vector conditional on the measurements, $p(\boldsymbol{X}_t|T_{0:t})$, and this probability distribution is represented by a set of random state samples called particles, which are denoted by

$$\boldsymbol{\Gamma}_t := \boldsymbol{X}_t^{[1]}, \boldsymbol{X}_t^{[2]}, \cdots, \boldsymbol{X}_t^{[M]} \tag{5}$$

with each particle $\boldsymbol{X}_t^{[m]} (1 \leq m \leq M)$ satisfying

$$\boldsymbol{X}_t^{[m]} \sim p(\boldsymbol{X}_t|T_{0:t}). \tag{6}$$

Then the minimum mean square estimate of $\boldsymbol{X}_t$ can be written as

$$\hat{\boldsymbol{X}}_t = \int \boldsymbol{X}_t p(\boldsymbol{X}_t|T_{0:t}) d\boldsymbol{X}_t. \tag{7}$$

Combining the motion model and measurement model derived, here represented by $p(\boldsymbol{X}_t|\boldsymbol{X}_{t-1})$ and $p(T_t|\boldsymbol{X}_t)$ respectively, the target distribution can be recursively calculated by [10]

$$p(\boldsymbol{X}_t|T_{0:t-1}) = \int p(\boldsymbol{X}_{t-1}|T_{0:t-1}) p(\boldsymbol{X}_t|\boldsymbol{X}_{t-1}) d\boldsymbol{X}_{t-1}, \tag{8}$$

$$p(\boldsymbol{X}_t|T_{0:t}) = c_t p(\boldsymbol{X}_t|T_{0:t-1}) p(T_t|\boldsymbol{X}_t). \tag{9}$$

where c_t is the normalization constant, given by

$$\frac{1}{c_t} = \int p(\boldsymbol{X}_t|T_{0:t-1}) p(T_t|\boldsymbol{X}_t) d\boldsymbol{X}_t. \tag{10}$$

Since the conditional distribution $p(\boldsymbol{X}_t|T_{0:t})$ can not be known *a priori*, the particles are generated from a proposal distribution. To offset the difference between the proposal distribution and the target distribution, particles $\boldsymbol{X}_t^{[m]}$ are weighted by

$$\omega_t^{[m]} = \frac{f(\boldsymbol{X}_t^{[m]})}{g(\boldsymbol{X}_t^{[m]})} = q(T_t^{[m]}, T_t) \tag{11}$$

which are normalized to

$$\omega_t^{[m]} = \frac{\omega_t^{[m]}}{\sum_m \omega_t^{[m]}}, \tag{12}$$

where f and g are the density functions of the target distribution and proposal distribution respectively. Because the travel time is a function of the glider's position, corresponding to each particle $\boldsymbol{X}_t^{[m]}$, there is a calculated value of travel time, denoted by $T_t^{[m]}$, which means that the weight is related to the deviation of travel time from the measurement T_t. The higher the wights, the higher the probability that the true state falls into the particles. As an approximation to Equation (7), take

$$\hat{\boldsymbol{X}}_t \approx \sum_{m=1}^{M} \omega_t^{[m]} \boldsymbol{X}_t^{[m]} \tag{13}$$

The re-sampling should be conducted to increase the percentage of particles with relatively high weights, that is the particles with lower importance weights are replaced by particles with higher weights. And after the re-sampling, the weights of particles are set to be equal: $\omega_t^{[m]} = 1/M$. While this re-sampling step is not always necessary except that the effective number of particles is less than a threshold [14]

$$N_{eff} = \frac{1}{\sum_m (\omega_t^{[m]}).^2} < N_{th}. \tag{14}$$

A numerical approximation of the particle filter implementation is given in the Algorithm 1. Because of the unknown currents, the real position may largely deviate from the dead-reckoning result in any direction. Thus the initial particles are distributed around the dead-reckoning position uniformly. In this case, the weight is given by

$$\omega_t^{[m]} = 1 - \frac{|T_t^{[m]} - T_t|}{\max |T_t^{[m]} - T_t|}. \tag{15}$$

Iteratively, the particles may concentrate on the true positions over time. To prevent the increased sample impoverishment problem which may result in that some $\omega_t^{[m]}$ converge to 1 and the filter would brake down, the roughening method [15] is introduced. The simulation analysis will be presented in the next section.

Algorithm 1 Particle filter implementation for dynamical localization of gliders

generate $\mathbf{X}_0^{[m]} \sim p\mathbf{X}_0, m = 1, 2, \cdots, M$
repeat
  calculate $T_t^{[m]}, T_t$ by BELLHOP
  compute $\omega_t^{[m]}$, N_{eff}
  estimate $\hat{\mathbf{X}}_t, \hat{\mathbf{V}}_t$
  set N_{th}
  if $N_{eff} < N_{th}$ **then**
    Resample M particles from $\boldsymbol{\Gamma}_t$
    let $\omega_t^{[m]} = 1/M$
    predict $\mathbf{X}_{t+1}^{[m]}$ by motion model.
  end if
  $t \leftarrow t + 1$
until $(t = t_{end})$

IV. Simulation Results

To dynamically localize the underwater gliders, the algorithm based on the particle filter is developed and the travel time of acoustic signals emitted by three near-surface sources is measured which is the only measurement used to modify the results of motion model. Fig. 3 is the sound speed calculated from the experiment data in the South China Sea which is set as the simulated environment.

In the horizontal coordinate system, the planar coordinates of three acoustic sources are $(0, 0)$, $(5km, 10km)$ and $(10km, 0)$ respectively. When any glider performs tasks in this region, it can receive acoustic signals from these sources, maybe not at the same time. Here, we set the receiving model as acquiring arrival signals sequentially, which means that at

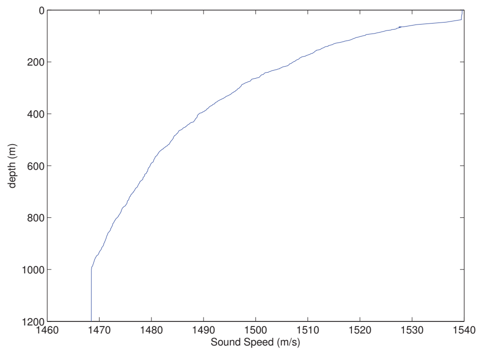


Fig. 3. Sound speed profile calculated from the experiment data in the South China Sea.

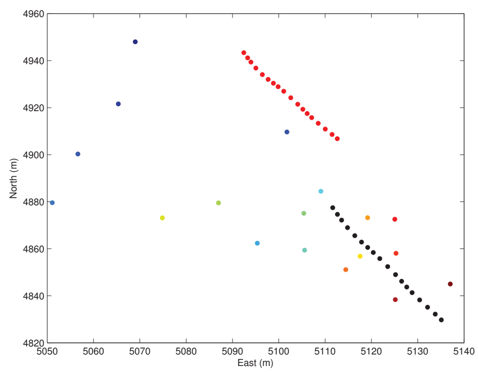
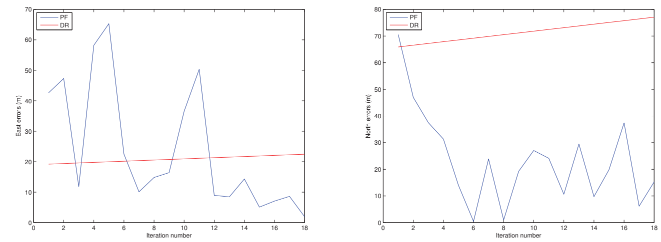


Fig. 4. Localization results: black dots are the true locations of the glider, red dots represent dead-reckoning results and the dots with gradient color are the estimated positions using the proposed method. The gradient color varies from blue to red over time.



(a) (b)

Fig. 5. The estimation errors of the glider's positions in (a) the east direction and (b) the north direction. The red line indicates the positioning error of the dead-reckoning algorithm, and the blue line represents the estimated error of the proposed PF based algorithm.

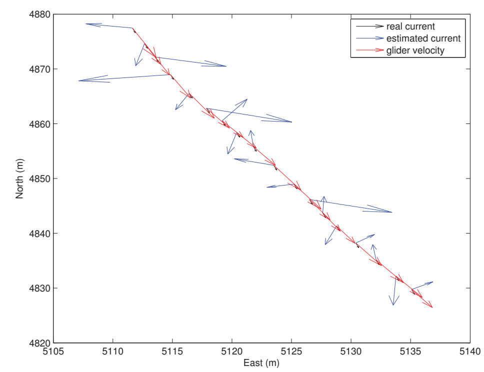


Fig. 6. Comparison of the velocity of currents. Red arrows represent the actual speed of the glider, black arrows denotes the real current and the currents derived from the estimated positions are represented by blue arrows.

each time point, the glider only receives signals from one acoustic source. The iteration cycle is set to 6s for each measurement, which means for each acoustic source, the cycle is 18s. By the Algorithm 1, the positions of gliders can be estimated on the condition that the initial particles are generated from evenly distributed random points around the dead-reckoning position. In details, considering that the initial time of the algorithm is set to 10min relative to the initial time of dead reckoning and the maximum value of the currents are generally no more than $0.8m/s$, the initial points are distributed within a circle of radius 500m.

Fig. 4 is the localization results. The red dots represent dead-reckoning results which are obviously deviated from the true locations of the glider, denoted by the black dots. The dots with gradient color varying from blue to red are the estimated positions over time using the proposed method. It can be seen that the estimated positions converge to the true points. Positioning errors are given in Fig. 5, which indicate that the proposed method can largely improve the positioning accuracy over time.

Depending on the estimated positions of the glider, the velocity of the currents can also be calculated iteratively by Equation (3). The estimated current vector is shown in Fig. 6. To compare these vectors more conveniently, all the vectors start at the real positions of the glider. In the initial phase, the estimated current is largely deviated from the actual current due to bad estimation results of the position. As the estimated result is updated iteratively, the calculated current gets close to the real current, which can in turn contribute to decrease the estimated errors of glider's positions. From this result, the feasibility of the estimate method for dynamical localization of gliders can be validated.

V. Conclusion

This paper has formulated a dynamic localization method based on the particle filter, and the only measurement parameter is the travel time of acoustic signals emitted by near-surface acoustic sources. The key idea is to estimate the most possible positions of gliders by comparing the travel time corresponding to predicted positions with the measurement. According to the calculated weights, the minimum mean square estimate of positions can be derived. Based on the estimated results of gliders' positions, the velocity of the currents can also be calculated iteratively, which can improve the predicted accuracy of the positions in turn. Simulation results indicate the effectiveness of this positioning algorithm for underwater gliders.

When the other marine vehicles develop the dead-reckoning algorithm, almost the same localization algorithm can be applied to achieve the positioning purpose. Future work may use this proposed method to localize any dead-reckoning based marine vehicles in an observation network. Furthermore, conduct experiments to improve the localization accuracy when some vehicle is assigned to perform a task in a certain interested region.

References

[1] B. Chen and D. Pompili, "Team formation and steering algorithms for underwater gliders using acoustic communications," *Computer Communications*, vol. 35, no. 9, pp. 1017–1028, 2012.

[2] J. C. Yu, A. Q. Zhang, W. M. Jin, Q. Chen, Y. Tian, and C. J. Liu, "Development and experiments of the sea-wing underwater glider," *China Ocean Engineering*, vol. 25, pp. 721–736, 2011.

[3] N. E. Leonard, D. A. Paley, R. E. Davis, D. M. Fratantoni, F. Lekien, and F. Zhang, "Coordinated control of an underwater glider fleet in an adaptive ocean sampling field experiment in monterey bay," *Journal of Field Robotics*, vol. 27, no. 6, pp. 718–740, 2010.

[4] B. Howe, T. McGinnis, and M. Boyd, "Sensor network infrastructure: moorings, mobile platforms, and integrated acoustics," in *Underwater Technology and Workshop on Scientific Use of Submarine Cables and Related Technologies, 2007. Symposium on*. IEEE, 2007, pp. 47–51.

[5] L. M. Brekhovskikh, *Fundamentals of Ocean Acoustics*, 1991, vol. 90, no. 6.

[6] J. J. Leonard, A. A. Bennett, C. M. Smith, and H. Feder, "Autonomous underwater vehicle navigation," in *IEEE ICRA Workshop on Navigation of Outdoor Autonomous Vehicles, Leuven, Belgium, May*. Citeseer, 1998.

[7] L. Techy, K. A. Morgansen, and C. A. Woolsey, "Long-baseline acoustic localization of the seaglider underwater glider," in *American Control Conference (ACC), 2011*. IEEE, 2011, pp. 3990–3995.

[8] L. J. Van Uffelen, E.-M. Nosal, B. M. Howe, G. S. Carter, P. F. Worcester, M. A. Dzieciuch, K. D. Heaney, R. L. Campbell, and P. S. Cross, "Estimating uncertainty in subsurface glider position using transmissions from fixed acoustic tomography sources," *The Journal of the Acoustical Society of America*, vol. 134, no. 4, pp. 3260–3271, 2013.

[9] H. Q. Huang, X. Y. Chen, H. Liu, and Y. Xu, "Improved unscented kalman filter based on decimation in frequency domain fast fourier transform for attitude estimation applied to underwater gliders," in *Applied Mechanics and Materials*, vol. 556. Trans Tech Publ, 2014, pp. 4372–4375.

[10] Y. Petillot, F. Maurelli, N. Valeyrie, A. Mallios, P. Ridao, J. Aulinas, and J. Salvi, "Acoustic-based techniques for autonomous underwater vehicle localization," *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, vol. 224, no. 4, pp. 293–307, 2010.

[11] S. Thrun, W. Burgard, and D. Fox, *Probabilistic robotics*. MIT press, 2005.

[12] H. C. Woithe, D. Boehm, and U. Kremer, "Improving slocum glider dead reckoning using a doppler velocity log," in *OCEANS 2011*. IEEE, 2011, pp. 1–5.

[13] M. B. Porter and H. P. Bucker, "Gaussian beam tracing for computing ocean acoustic fields," *The Journal of the Acoustical Society of America*, vol. 82, no. 4, pp. 1349–1359, 1987.

[14] N. Bergman, "Recursive bayesian estimation," *Department of Electrical Engineering, Linköping University, Linköping Studies in Science and Technology. Doctoral dissertation*, vol. 579, 1999.

[15] N. J. Gordon, D. J. Salmond, and A. F. Smith, "Novel approach to nonlinear/non-gaussian bayesian state estimation," in *Radar and Signal Processing, IEE Proceedings F*, vol. 140, no. 2. IET, 1993, pp. 107–113.