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Moving Horizon Estimation for Moving Long Baseline based on Linear Positioning Model ⋆

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Abstract: This paper presents the real-time moving horizon estimation (MHE) for Moving Long Baseline (MLBL) positioning system. By establishing the linear positioning model, we formulate MLBL positioning problem in a linear, time-invariant, discrete-time system. In this system, we assume that the velocity of Autonomous Underwater Vehicle (AUV) is known, and the distances between Unmanned Surface Vessels (USVs) and AUV are the measurements. Then, we design a moving horizon estimator with the dynamic model and state constrains are considered. This estimator determines the position of AUV by solving a constrained optimization problem. The estimated positions are computed by minimizing the cost function. Simulation results demonstrate the performance of the MHE algorithm with the comparison of Kalman Filter (KF).

Keywords: moving long baseline, autonomous underwater vehicle, moving horizon estimation, position estimation.

1. INTRODUCTION

Since the underwater environment is complex and access-constrained, the precise position of the underwater vehicles is unavailable Erol-Kantarci et al. (2011). Therefore, the acoustic based positioning systems have been sought in the past, including systems such as Long Baseline (LBL) Whitcomb et al. (1999); Ahn et al. (2003), Short Baseline (SBL) Smith and Kronen (1997); Wolbrecht et al. (2013), and Ultra-Short Baseline (USBL) Rigby et al. (2006); Kinsey et al. (2006). In these systems, LBL can achieve the highest positioning accuracy, but it has several shortcomings, e.g., requiring long time for calibration, hard to place and recover the seabed transponders, and limited operating region Vaganay et al. (2004); Curcio et al. (2005); Folk et al. (2010). Moving long baseline (MLBL) is generalized from LBL and it overcomes the shortcomings of LBL described above Caiti et al. (2005); Alcocer et al. (2007). Recent works on MLBL can be found in Bahr et al. (2009); Fallon et al. (2010); Bishop et al. (2010); Moreno-Salinas et al. (2013).

In MLBL, the position of Autonomous Underwater Vehicle (AUV) is determined by the positions of Unmanned Surface Vessels (USVs) and the distance measurements between AUV and USVs. Based on the measurements of distance and distance difference, the circle-based model and the hyperbola-based model are commonly used to estimate the position of AUV Bian et al. (2010); Tan et al. (2011). However, these two kinds of models are nonlinear. Hence, we present a linear positioning model on the basis of the circle-based model. By using this model, we can reduce the complexity of the algorithm and the computation.

In past few years, many distance-based positioning algorithms have been proposed in the literature, such as Maximum Likelihood Estimation (MLE) Howard et al. (2002), Kalman Filter (KF) Olson et al. (2006); Techy et al. (2011); Batista et al. (2010) and Particle Filter (PF) Fox et al. (2000). Among these filters, prior estimation and current measurement are used to estimate the current state. Similar to KF, Moving Horizon Estimation (MHE) is based on the least-squares cost function. However, MHE considers a finite moving horizon of measurements information into the estimation problem. And it can deal with the constraints on the estimation Haseltine and Rawlings (2005).

The stability analyses about MHE for linear and nonlinear systems are in Rao et al. (2001, 2003). For recent years, MHE has been applied to many fields. In Vandersteen

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et al. (2013), the nonlinear numerical observer for attitude estimation is presented. In Wang et al. (2014), the MHE is applied to locate AUV by using a single surface mobile beacon. More details about MHE can be seen in Rawlings (2015).

In this paper, by using MHE method, a finite moving horizon of measurements information is used to estimate the position of AUV. Firstly, we establish a linear positioning model for MLBL. Then, the cost function is designed with the constrains are considered. Finally, the positions are estimated by minimizing this cost function.

The paper is structured as follows. Section 2 presents the positioning model of MLBL. The cost function of MHE is discussed in Section 3. Section 4 compares the simulation results between KF and MHE. Finally, we conclude our work in Section 5.

2. POSITIONING MODEL

2.1 Overview of MLBL

As shown in Fig. 1, USVs are equipped with acoustic transponders, GPS, wireless communications, and AUV is equipped with transponders. Firstly, AUV sends an acoustic query ping. Then, after receiving a query ping from AUV, each USV sends out a reply ping on its individual transmit channel. The reply ping contains the position information of each USV, respectively. Finally, AUV receives the reply pings. By multiplying the One-Way Travel Time (OWTT) of the acoustic pings and the sound speed, the distances between AUV and USVs is calculated. The position of AUV can be estimated by the positions of USVs and these distances.

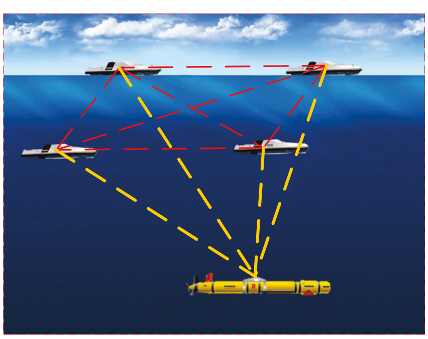

Fig. 1. MLBL system consists of 4 mobile buoys.

2.2 Kinematics Model

As shown in Fig. 2, consider an earth fixed reference frame $\{O\} := \{x_0, y_0, z_0\}$ with $z = 0$ on the water surface, and the z-axis pointing downward from the water surface. Supposing there are four USVs on the water surface, the coordinate of AUV at stamp k is (x_k, y_k, z_k). Then, the kinematics model of AUV is described as

$$\begin{cases} x_{k+1} = x_k + T_s v_{xk} = x_k + T_s v_k \cos\psi_k \cos\theta_k, \\ y_{k+1} = y_k + T_s v_{yk} = y_k + T_s v_k \sin\psi_k \cos\theta_k, \\ z_{k+1} = z_k + T_s v_{zk} = z_k + T_s v_k \sin\theta_k, \end{cases}$$

where T_s is the sampling period, v_k is the velocity, ψ_k is the yaw, θ_k is the pitch. v_{xk}, v_{yk} and v_{zk} are the velocities in x-axis, y-axis and z-axis, respectively.

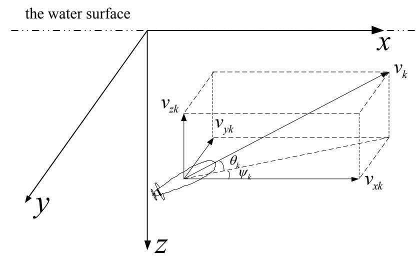

Fig. 2. Kinematics model of AUV.

2.3 Positioning model

Assuming that the coordinate of USVi at stamp k is $(x_{i,k}, y_{i,k}, z_{i,k})$ and the distance measurement between USVi and AUV is $r_{i,k}$. Then, the distance between them should satisfy

$$(x_k - x_{i,k})^2 + (y_k - y_{i,k})^2 + (z_k - z_{i,k})^2 = r_{i,k}^2.$$

Define $r_{j,k}$ is the distance between USVj and AUV. Similarly, we have

$$(x_k - x_{j,k})^2 + (y_k - y_{j,k})^2 + (z_k - z_{j,k})^2 = r_{j,k}^2.$$

USVs are on the water surface, then we obtain

$$z_k - z_{i,k} = z - z_{j,k}.$$

It follows that

$$\begin{aligned} r_{i,k}^2 - r_{j,k}^2 = &- 2\left(x_{i,k} - x_{j,k}\right) x_k - 2\left(y_{i,k} - y_{j,k}\right) y_k \\ &+ x_{i,k}^2 + y_{i,k}^2 - x_{j,k}^2 - y_{j,k}^2. \end{aligned} \tag{1}$$

Hence, the positioning model is transformed into a linear equation in two unknowns. It can reduce the complexity of the positioning algorithm and the computing time.

3. POSITIONING ALGORITHM

3.1 Linear discrete-time system

Define $\boldsymbol{x}_k := (x_k, y_k)^{\mathrm{T}}$ as the state of the system. According to the kinematics model of AUV, the process equation is written as

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{B}\boldsymbol{u}_k + \boldsymbol{w}_k, \tag{2}$$

where $\boldsymbol{B} := \mathrm{diag}\{T_s, T_s\}$ and $\boldsymbol{u}_k := (v_{xk}, v_{yk})^{\mathrm{T}}$. $\boldsymbol{w}_k := (w_{1,k}, w_{2,k})^{\mathrm{T}}$ is the process noise. From Eq. (1), the measurement equation is expressed as

$$\boldsymbol{y}_k = \boldsymbol{C}_k \boldsymbol{x}_k + \boldsymbol{D}_k + \boldsymbol{v}_k. \tag{3}$$

where $\boldsymbol{v}_k := (v_{1,k}, v_{2,k})^{\mathrm{T}}$ is the measurement noises,

$$\boldsymbol{y}_k = \begin{bmatrix} r_{1,k}^2 - r_{2,k}^2 \\ r_{2,k}^2 - r_{3,k}^2 \\ r_{3,k}^2 - r_{4,k}^2 \end{bmatrix},$$

$$\boldsymbol{C}_k = -2 \begin{bmatrix} (x_{1,k} - x_{2,k}) & (y_{1,k} - y_{2,k}) \\ (x_{2,k} - x_{3,k}) & (y_{2,k} - y_{3,k}) \\ (x_{3,k} - x_{4,k}) & (y_{3,k} - y_{4,k}) \end{bmatrix},$$

$$\boldsymbol{D}_k = \begin{bmatrix} x_{1,k}^2 + y_{1,k}^2 - x_{2,k}^2 - y_{2,k}^2 \\ x_{2,k}^2 + y_{2,k}^2 - x_{3,k}^2 - y_{3,k}^2 \\ x_{3,k}^2 + y_{3,k}^2 - x_{4,k}^2 - y_{4,k}^2 \end{bmatrix}.$$

In MLBL, the positions of USVs can be gained through the reply pings. The distances between USVs and AUV are the measurements. Hence, $\boldsymbol{C}_k$ and $\boldsymbol{D}_k$ are known matrices, $\boldsymbol{y}_k$ can be seen as the measurement. Combining Eq. (2) with Eq. (3), we establish a linear, time-invariant, discrete-time system.