Research and Application of Submersible Position Prediction Model Based on Kalman Filtering

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Abstract. In this study, a positioning prediction model is proposed for the submersible position prediction problem based on the Kalman filter algorithm. First, the problem is analyzed to determine the uncertainty factors involved in the prediction of the position of the submersible, such as the propulsion of the submersible, ocean currents, seawater density and seabed topography. Subsequently, a position prediction model based on Kalman filtering algorithm is established, including the steps of state definition, system dynamic model, observation model, definition of initial state and covariance matrix, Kalman gain calculation, state update, and state prediction at the next moment. For the equipment requirements involved in the model building process, the factors affecting the position prediction of the submersible are analyzed and the corresponding equipment requirements are proposed. Finally, Python software is utilized for model fitting and prediction, and the fitting accuracy of the model is evaluated by mean square error and mean absolute error, and the results show that the model has a good fitting effect.

Keywords: Kalman filter, Submersible, Position prediction.

1. Introduction

The exploration of the underwater world is colorful, but it also contains many unknown dangers. A Greek company has a submersible that can go to the deepest part of the ocean and take tourists to the wonders of the underwater world[1-2]. With the increasing development of marine resources and scientific research, there is a growing demand for accurate positioning of submersibles in the ocean[3]. However, the complexity and uncertainty of the marine environment bring great challenges to the prediction of submersible position. To solve this problem, this study proposes a submersible position prediction model based on the Kalman filter algorithm. Kalman filtering, as a recursive state estimation algorithm, has a wide range of applications in dealing with dynamic systems, and it can effectively integrate multi-sensor data and improve the accuracy of state estimation. In this study, we first analyze the various uncertainty factors affecting the position prediction of a submersible, and then establish a Kalman filter-based position prediction model, taking into account the equipment requirements needed for the submersible. Finally, we performed model fitting and prediction using the model, and the results show that the model has good fitting accuracy and prediction effect. The results of this study are of great theoretical and practical significance for improving the accuracy of positioning of submersibles in the marine environment[4-5].

2. Localization prediction model based on Kalman filter algorithm

2.1. Problem analysis

The prediction of the position of the submersible involves a number of uncertainties, including the propulsion force of the submersible, the influence of ocean currents, different densities in the sea and the geographical environment of the seabed. Therefore, a model needs to be built to account for these uncertainties and predict the position of the submersible. For example, as shown in figure 1, the intricate and uncertain topography of the Ionian sea floor can be seen in the following 3d elevation model, and the dangers of the deep sea are unfathomable, so we should all be in awe of nature. Kalman filter is a recursive state estimation algorithm, which is widely used in dynamic systems, especially in linear systems. In the submarine position prediction problem, Kalman filter can effectively integrate multi-sensor data, such as GPS and depth sensor on the submarine, so as to improve the estimation accuracy of the state, which is particularly important for the submarine in the Marine environment[6].

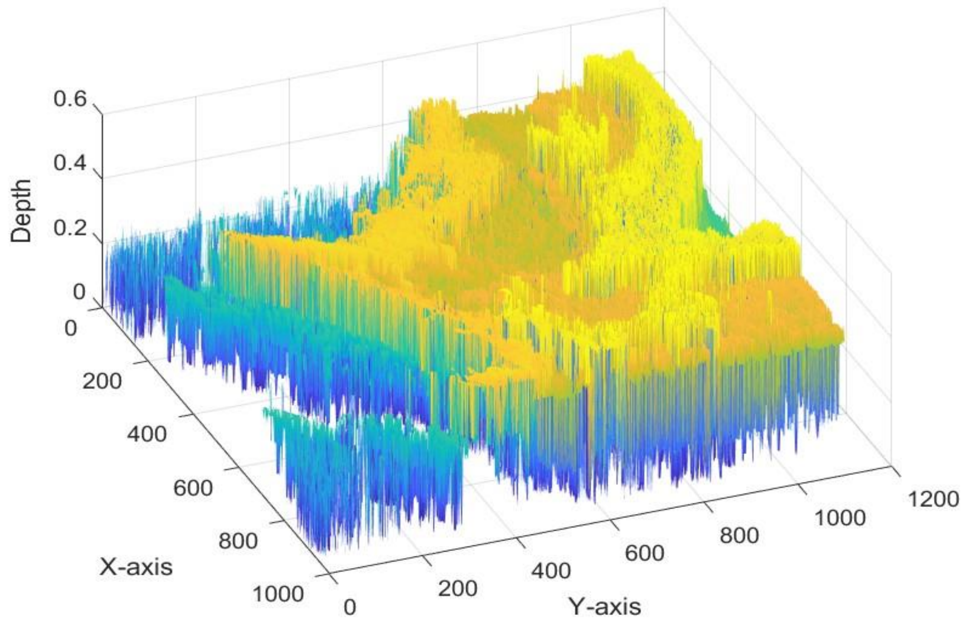

Figure 1: 3D elevation modeling diagram

2.2. Model building

Kalman filter is an optimal estimation algorithm based on the linear system and Gaussian noise hypothesis, which is often used to estimate the state variables of a system and can give reasonable results even if it is affected[7-8].

1. State definition:

The team defined the submarine's state as a state vector containing position and velocity, expressed as

$$X_t = [x_t, v_t]^T \tag{1}$$

2. System dynamic model:

Since the system dynamic model is a model that describes the balance relationship between the components of the system and the system and the outside world as well as the motion process of these relations, it can reflect the dynamic characteristics of the interaction of various factors in the process of movement change of the system. The team established the submarine's motion equation, using a simple uniform linear motion model

$$X_{t+1} = F \cdot X_t + B \cdot U_t + \varepsilon_t \tag{2}$$

3. Observation model:

In order to predict the submarine's position, the team defined an observation equation that shows how the state of the submarine can be observed through sensors

$$Z_t = H \cdot X_t + \delta_t \tag{3}$$

4 Initial state and covariance matrix:

Since the location of the submarine was decided by man, the team adopted the Delta method to define the initial state estimate of the submarine as X0. Taking into account the influence of ocean currents and submarine topography analyzed in 4.1, the team constructed the initial covariance matrix P0, which is the estimate of the initial uncertainty of the submarine state

5. Kalman gain calculation:

The team calculated the Kalman gainK_t using a system dynamic model and an observational model:

$$K_t = P_t \cdot H^T \cdot (H \cdot P_t \cdot H^T + R)^{-1} \tag{4}$$

6. Status Update:

The team used observations and Kalman gains to update the state estimates and covariance matrix:

$$X_t = X_t + K_t \cdot (Z_t - H \cdot X_t) \tag{5}$$

$$P_t = (I - K_t \cdot H) \cdot P_t \tag{6}$$

7. Predict the state of the next moment:

The team uses the system dynamic model to predict the state:

$$X_{t+1} = F \cdot X_t + B \cdot U_t \tag{7}$$

$$P_{t+1} = F \cdot P_T \cdot F^T + Q \tag{8}$$

According to the factors affecting the prediction of submarine position discussed by the team in the problem analysis, taking into account the influence of ocean current, sea water density and temperature, and seabed topography, the submarine can send GPS signals to the main ship regularly before the accident to determine the initial position. In order to predict the accurate position, the submarine should also send temperature and current velocity regularly. Density and other indicators to reduce errors, for which the team relied on remote sensing technology get the data.

Table 1. Related device specifications

equipment	index	unit	Expect the normal range
Acoustic Doppler current profiler(ADCP)	Water velocity	Meters per second (m/s)	**0 - 2 m/s**[1]
	Water temperature	Degrees Celsius (°C)	**-2 - 35 °C**[2]
Conductivity, temperature, depth sensor(CTD)	salinity	dimensionless	**33 - 37 PSU**[2]
	profundity	Meters (m)	**Varies greatly, depending on the sea**
drifting buoy	Sea surface velocity	Meters per second (m/s)	**0 - 2 m/s**[3]
	Sea surface temperature	Degrees Celsius (°C)	**-2 - 35 °C**[3]
	Sea surface temperature	Degrees Celsius (°C)	**-2 - 35 °C**[4]
	Sea surface height	Meters (m)	**Big change, depending on sea level**
Remote sensing satellite sensor	Sea surface salinity	dimensionless	**33 - 37 PSU**[4]
	Sea surface wind speed	Meters per second (m/s)	**0 - 20 m/s**[4]
	Sea height	Meters (m)	**0 - 15 m**[4]

2.3. Model fitting

Mean square error (MSE) and mean absolute error (MAE) are two commonly used indicators to evaluate the fitting effect of a model. MSE is the average of the square difference between the predicted data and the original data, and MAE is the average of the absolute difference between the predicted data and the original data. They are calculated as follows:
Among them:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2$$
$$MAE = \frac{1}{n}\sum_{i=1}^{n}| y_i - y_i | \tag{9}$$

n is the number of samples, y_i stands for raw data, y_i indicates the prediction result

Predictions are made using python software by recursively applying the above steps of the Kalman filter algorithm. With the support of the python extension library, we get the following prediction renderings, and we get the following two model accuracy tests MAE: 0.110, MSE: 0.032, It shows that the model has good fitting precision. According to the following prediction effect figure 2, it can be seen that the prediction fitting effect is good[9-10].

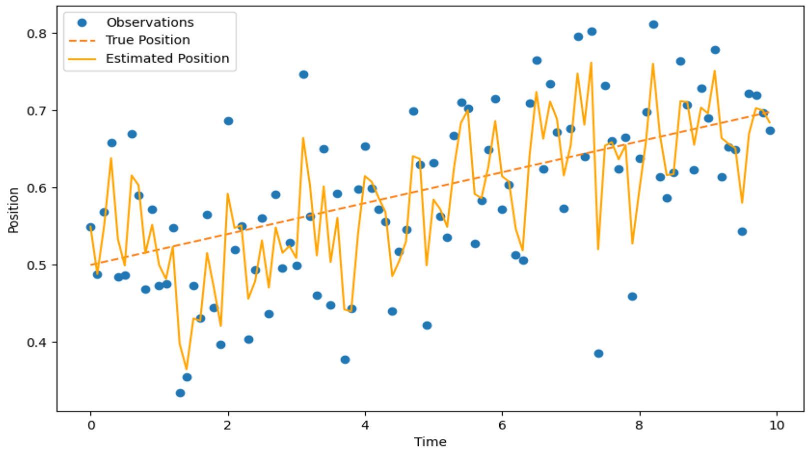

Figure 2: Kalman filter position prediction diagram

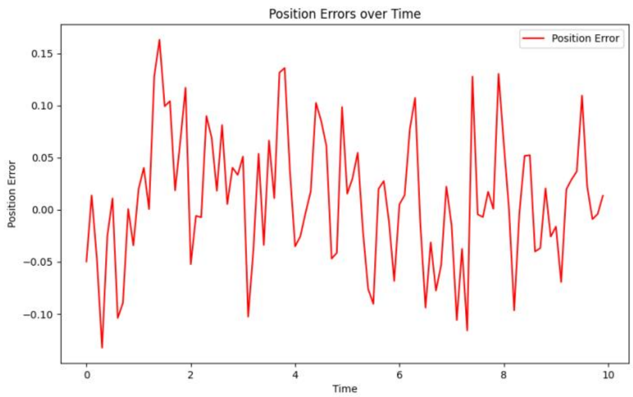

Figure 3: Error plot

Figure 3 shows that the model has good fitting precision. According to the following prediction effect diagram, it can be seen that the prediction fitting effect is good. Plot the error curve between the estimated position and the true position in order to understand the accuracy of the Kalman filter.

It can be seen from the graph of the error curve with time that the error changes in a small range but the value of the fluctuation is small, and the accuracy of the model is high.

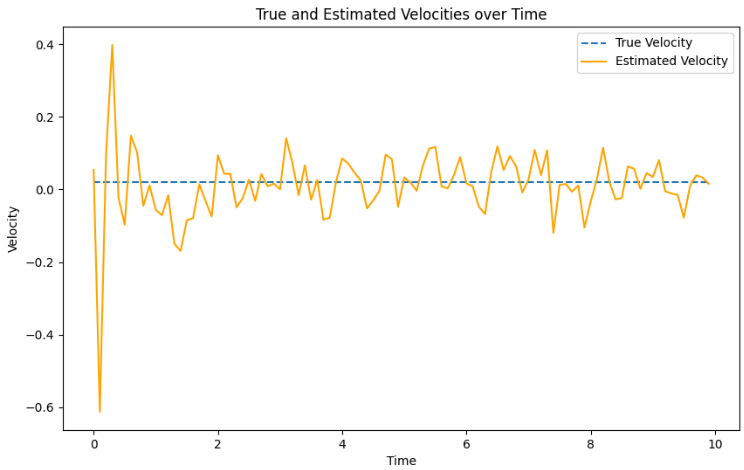

Figure 4: Comparison chart of velocity estimates

To compare real and predicted speeds, we use a line chart to show how these two sets of data change over time,as shown in figure 4. The horizontal axis represents time, and the vertical axis represents speed. The real speed data is shown as a dashed line, and the real speed is shown as a solid line. As can be seen from the figure above, the value of the predicted velocity changes gradually from large fluctuation to small fluctuation over time, and the fitting effect with the real velocity is better as time goes on.

3. Conclusions

Through this study, a submersible position prediction model based on Kalman filter algorithm is successfully established. The model effectively integrates multi-sensor data to improve the accuracy and stability of the predicted position of the submersible, based on the consideration of various uncertainties in the marine environment. The model is validated by fitting and prediction, and shows good fitting accuracy and prediction effect, providing reliable technical support for marine scientific research, resource exploration and submersible rescue. In the future, the model can be further optimized to improve the prediction accuracy and promote the development and application of submersible technology in the marine field.

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