Research on Ocean Current Prediction Based on POD-LSTM Hybrid Model

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Abstract. Although ocean current prediction is crucial to climate, ecology, and shipping, its complex nonlinear characteristics make it difficult to predict accurately by traditional methods. Advances in ocean observation technology have opened up new ways for data-driven models. In general, in this study, the data set was decomposed into average snapshots by Reynolds decomposition Matrix and pulsation snapshot matrix, and POD decomposition of pulsation, and then introduced Long Short-Term Memory (LSTM) to predict the ocean current, and then obtains the ocean current prediction model, and then uses the resulting ocean current model to find a missing submarine that lost contact and power and predict the location of the submarine. Then, a submarine model is established to predict the position of the submarine by applying the ocean current model and the principle of fluid mechanics. The accuracy and practicability of the ocean current prediction model are demonstrated by comparing the prediction results with the actual results The uncertainty of the predicted results of the model was only26.7837%. From the data, it can be seen that the model predicts better with smaller trajectory offsets.This experiment shows the feasibility of applying LSTM neural network combined with POD decomposition to the field of ocean current prediction, and also provides experience for applying more methods of machine learning to the field of navigation and sea in the future.

Keywords: POD decomposition, Long Short-Term Memory, the ocean current prediction model.

1. Introduction

As one of the largest fluid movement systems on the earth's surface, ocean currents have an important impact on global climate regulation, Marine ecosystem, shipping safety and Marine resources development. Accurate prediction of the temporal and spatial characteristics of ocean currents is not only of great scientific significance but also of great practical value. However, the ocean current system is highly nonlinear and uncertain, and the traditional forecasting methods are difficult to meet the high precision requirements. The main challenge is that ocean currents are affected by a variety of factors, such as weather changes, human activities, and seabed topography. The spatial and temporal distribution of Marine data is not uniform; The velocity field of ocean current exhibits complex multi-scale characteristics. With the development of ocean observation technology, the ability of data acquisition has been greatly improved, which provides the possibility of a data-driven ocean current prediction model.

At present, in addition to the traditional prediction method of simulating water movement through numerical models, many domestic scholars[1-8] have tried to apply neural networks to ocean tide analysis and prediction, and verified the feasibility of using neural networks to predict water flow time series. In order to better study the impact jet, Wang Bo and his research team introduced POD decomposition to identify the dominant spatial features of the impact jet and provide the time series information of the corresponding modes to facilitate the analysis of the spatio-temporal changes of the impact jet atomization[9]. Therefore, this study also attempts to introduce POD decomposition to get the dominant features affecting ocean currents, and cooperate with LSTM neural network, so as to facilitate the establishment of ocean current models.

In this work, this study first collected the velocity and direction information of ocean currents at different depths in previous years in a randomly selected sea area (Copernicus Sea area in this case). To eliminate the influence of other factors, POD decomposition was adopted for this original data set, and it was divided into the completely time-dependent part and the space-dependent part. In this study, the time component is used to predict the speed of ocean currents. Then, this study completed the construction of the ocean current prediction model by introducing the LSTM neural network. Next, by combining the ocean current prediction model, the analysis of the submarine model, and the principle of fluid mechanics, the team obtained the position prediction model of the missing submarine in the sea area[10]. By comparing the prediction results with the actual results, the accuracy of the position prediction model was obtained.

2. Ocean Current Data Processing and POD Dimensionality Reduction Analysis

2.1. Ocean Current Data Processing

The Data source of this paper is the ocean current data set of the target area over the past years in the Copernicus Marine Data Store. The data mainly includes the velocity and direction of ocean currents at different depths.

In terms of spatial dimensions, our dataset has latitude and longitude ranging from $18°E$ to $20°E$ and $37°N$ to $39°N$, respectively. The paper plotted Figure 1, a 3D topographic map, based on the data from the Gridded Bathymetry Data.

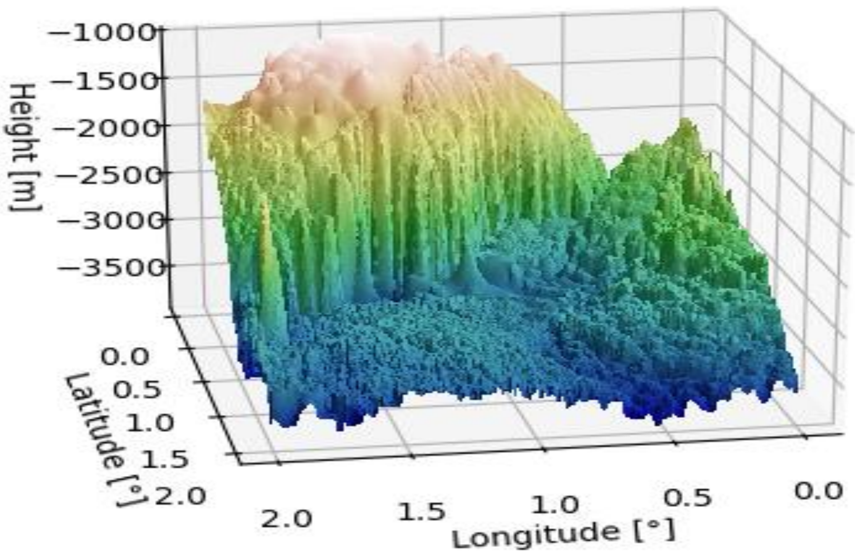

Figure 1. Velocity map of ocean currents

In terms of the time dimension, the prediction of the ocean density is done by calculating the density from temperature, salinity, pressure, and other data from the Ocean Data Center of the Institute of Oceanography of the Chinese Academy of Sciences, which covers the last 50 years of such data. The study plotted a velocity map of ocean currents as shown in Figure 2. LSTM neural network is used for all the predictions in the above data set. The LSTM method flow chart is shown in Figure 3.

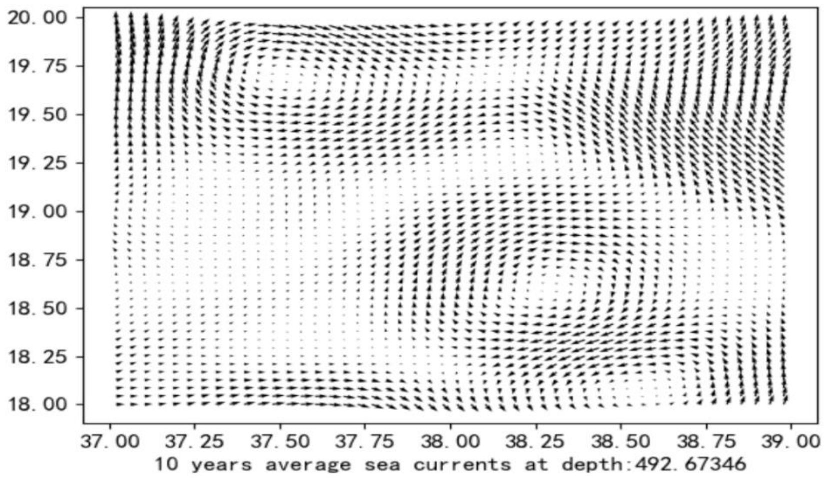

Figure 2. Velocity map of ocean currents

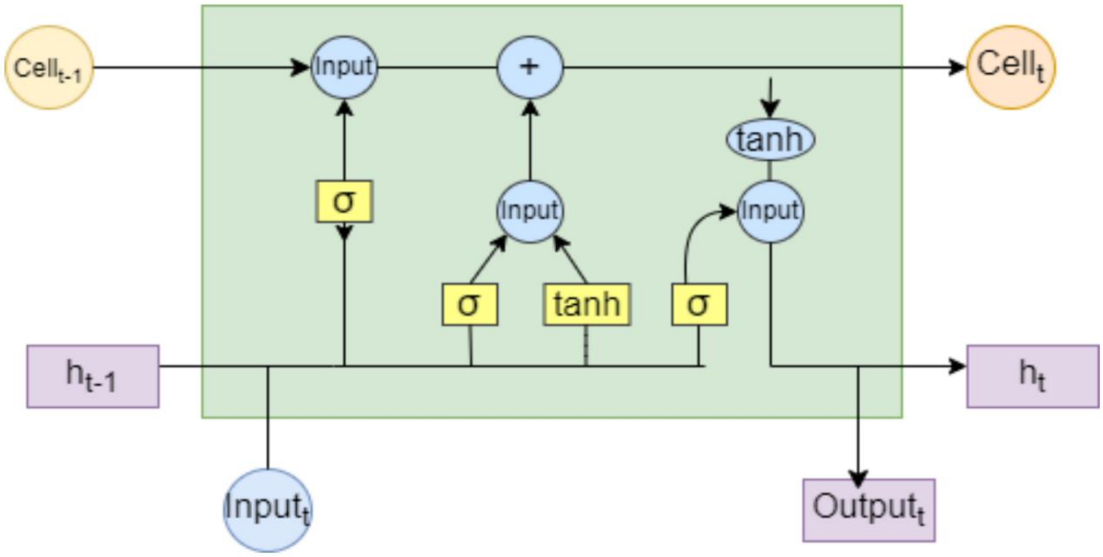

Figure 3. Flowchart of LSTM method

Before employing LSTM, data processing, and feasibility verification are essential. Traditional forecasting methods involve analyzing the historical variability of each data point to predict potential values at some point in the future. Subsequently, these discrete results are used to update our current parameters. However, this approach lacks rigor. The speed of ocean currents can be significantly influenced by various factors, such as the movement of human vessels, weather, and climate conditions, and the migration of large schools of fish on the seafloor.

To eliminate the aforementioned anomalous irregular values, the study needs to use a method that minimizes the impact of random events. Hence, this work employs the Proper Orthogonal Decomposition (POD) method for the model. In this method, the paper divides the original data set into two parts - one that is solely time-dependent and the other that is spatially-dependent. In the case, where the goal is to predict the future position of the submersible, the study predicts the velocity of ocean currents by forecasting the temporal part.

2.2. POD Dimensionality Reduction Analysis

The snapshots referred to in this topic contain latitude, longitude, depth data, and ocean velocity direction for all data points at a given moment in time.

$$\vec{S}_i = [d_1, d_2, d_3 \cdots, d_n] = ST(\vec{x}, t) \tag{1}$$

$$U=[\vec{s}_1,\vec{s}_2,\cdots,\vec{s}_m]^T=U(\vec{x},t) \tag{2}$$

Given each vector $\vec{S}_i$, which contains n data points. It is related to the space $\vec{x}$ and time t quantities. The whole data sets U is a matrix containing m snapshots.

By Reynolds decomposition, this snapshot matrix class is decomposed into an average snapshot matrix and pulsating snapshot matrix, and it has performed POD decomposition for the pulsating snapshot matrix.

$$\cup(\vec{x},t)=\vec{\cup}(\vec{x},t)+\cup'(\vec{x},t) \tag{3}$$

$$U'(\vec{x},t)=\sum_{i=1}^{m}a_i(t)\cdot\Phi_t(\vec{x})=[\Phi_1(x)\Phi_2(x)\Phi_3(x)\cdots\Phi_m(x)]\begin{bmatrix}a_1(t)\\a_2(t)\\\vdots\\a_m(t)\end{bmatrix} \tag{4}$$

where $\Phi_i(x)$ is the spatial modality of the POD, also called the POD basis, which is related to the space $\vec{x}$. $a_i(t)$ are the modal coefficients corresponding to the modules of each order, also

called the temporal coefficients, which are related to the time t only.

$$\Phi_i(x)\cdot\Phi_j(x)=\begin{cases}0 & i\neq j\\1 & i=j\end{cases} \tag{5}$$

The goal of POD is to find an optimal set of pod bases $\Phi 1(x)\Phi 2(x)\Phi 3(x)\cdots\Phi m(x)$ such that the pulsation values at any moment on any node of the constructive model can represent a linear combination of POD bases.

$$\begin{aligned}\hat{U}'(\vec{x},t)&=a_1(t)\Phi_1(x)+a_2(t)\Phi_2(x)+\cdots+a_n(t)\Phi_n(x)\\&=[\Phi_1(x)\Phi_2(x)\Phi_3(x)\cdots\Phi_m(x)]\begin{bmatrix}a_1(t)\\a_2(t)\\\vdots\\a_m(t)\end{bmatrix}\end{aligned} \tag{6}$$

In order to ensure the accuracy of the modal interception process, the first-order modes should be chosen such that the error between $\widehat{U}'(\vec{x},t)$ and $U(\vec{x},t)$ is minimized.

$$error=\left[\left(U'\left(\vec{\lambda},t\right)-\hat{U}'(x,t)\right)^T\left(U'(\vec{x},t)-\hat{U}'(x,t)\right)\right] \tag{7}$$

$$error=\sum_{i=n+1}^{m}\lambda_i \tag{8}$$

That is, the individual eigenvalues can be calculated from a, arranged from largest to smallest. The largest possible eigenvalues of the previous eigenvalues make the modal interception process more accurate. The larger the eigenvalue the larger the energy of the corresponding pod mode. Details are given in Table 1 below.

Table.1. The first six eigenvalues

eigenvalue	Percentage of eigenvalues
0.74998426	0.39813003
0.45794818	0.24310233
0.2424395	0.12869929
0.16480313	0.08748594
0.1380024	0.07325874
0.0729484	0.03872474

Since the proportion of the sum of the first five eigenvalues is 93% of the sum of all eigenvalues. Therefore, next it can discard the modes with smaller eigenvalues and keep only the first five modes.

$$U'(\vec{x},t) \approx \hat{U}'(x,t) = a_1\Phi_1(x) + a_2\Phi_2(x) + a_3\Phi_3(x) + a_4\Phi_4(x) + a_5\Phi_5(x) \tag{9}$$

To validate the precision of our model, we partitioned the original data set into two distinct subsets: the training set and the test set. The training set underwent learning processes exclusively based on five distinct modalities. Subsequently, the study employed these learned modalities to predict outcomes for the test set. The resultant predictions were meticulously compared against the actual values, allowing us to quantify the model's relative error. The detailed results are presented below: Figure 4-8

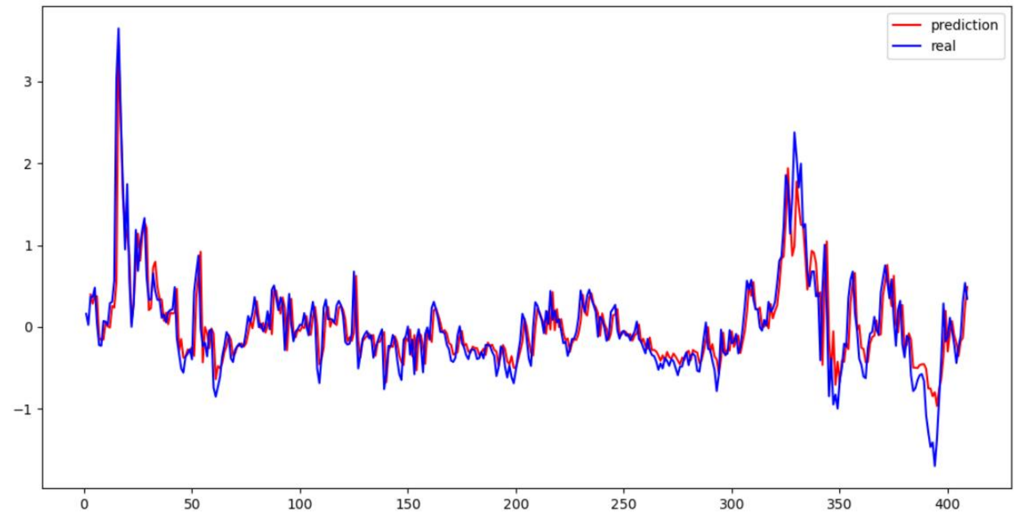

Figure 4. Component 1

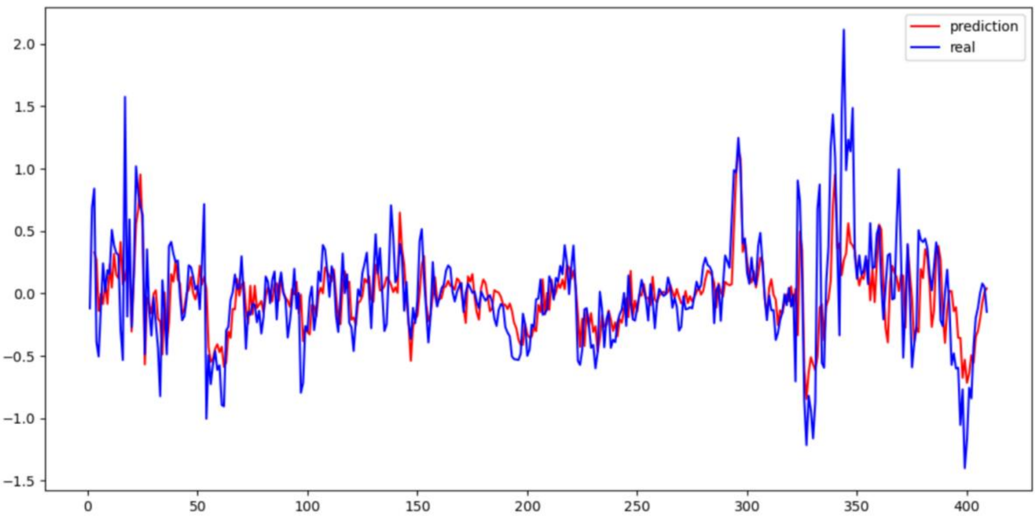

Figure 5. Component 2

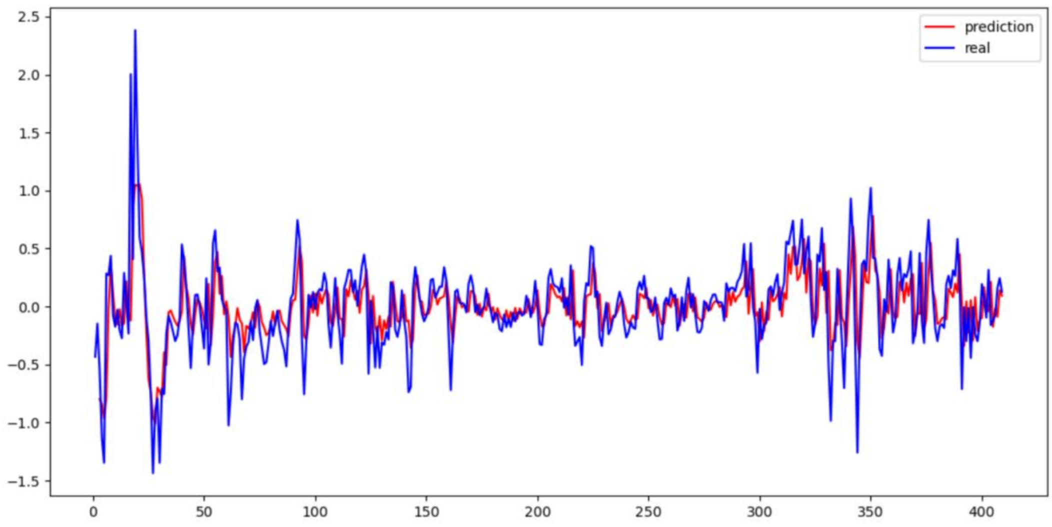

Figure 6. Component 3

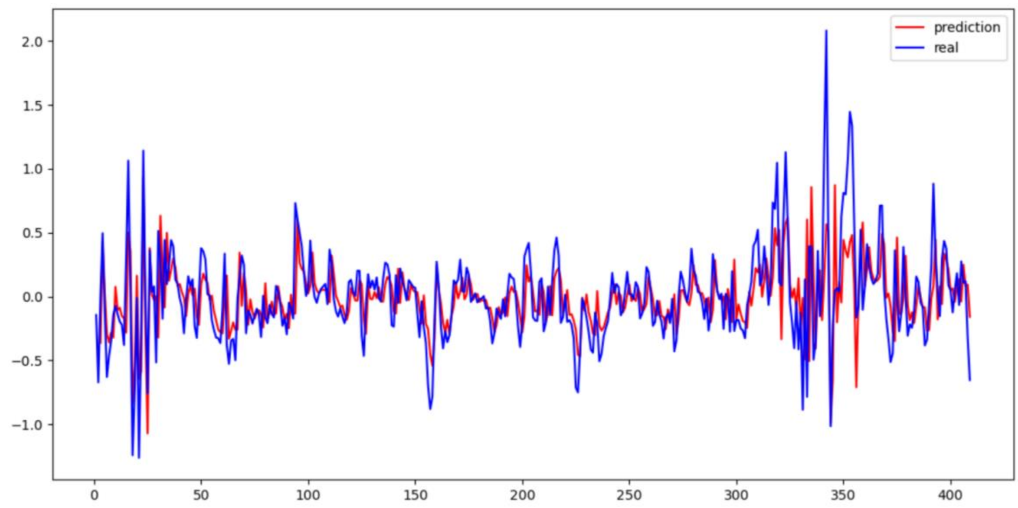

Figure 7. Component 4

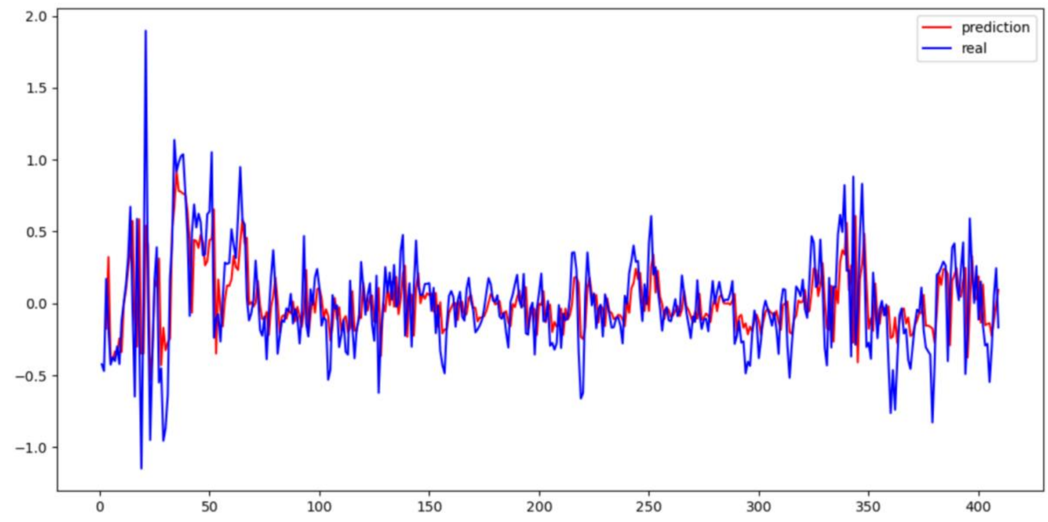

Figure 8. Component 5

The above images 4-8 respectively show the visual display of the deviation between the predicted 5 results and the actual situation. The X-axis represents the elapsed time (in days) and the Y-axis represents the magnitude of the scaled value of the ocean velocity. The red curve represents the change curve of ocean current velocity predicted by the model with time, and the blue curve represents the change curve of actual ocean current velocity with time. It can be seen that the predicted results are basically consistent with the actual results.

3. Mechanical Model and Uncertainty Analysis of Submersible in Ocean Current Environment

3.1. Velocity analysis of ocean currents

The study analyzes the problem based on an inertial reference system as follows:

$$V_m = \begin{pmatrix} v_{mx} \\ v_{my} \\ v_{mz} \end{pmatrix} = \begin{pmatrix} v_m \cos\varphi_m \cos\theta_m \\ v_m \sin\psi_m \cos\theta_m \\ -v_m \sin\theta_m \end{pmatrix} \quad (10)$$

However, for easier and more convenient calculations we need to convert the current velocity into a velocity in the submersible's coordinate system.

$$V_m{}' = \begin{pmatrix} V_{mx}{}' \\ V_{my}{}' \\ V_{mz'} \end{pmatrix} = T^{-1} V_m \quad (11)$$

It can then derive the relative velocity of the submersible to the current in the submersible navigation coordinate system.

$$Va = v - vm' \quad (12)$$

3.2. Mechanical analysis of submersibles

For the model of the submersible, It can think of it as the rectangular body shown above, and from the principles of hydrodynamics it can derive the force on the submersible in the x-direction as:

$$dF_x = \frac{1}{2} \rho V_{ax}^2 \cdot ds \quad (13)$$

$$ds = a \cdot dh \quad (14)$$

$$F_x = \frac{1}{2} a \sum_{i=1}^{n} \rho_i v_{axi}{}^2 \Delta h_i \quad (15)$$

$$\sum_{i=1}^{n} \Delta h_i = a \quad (16)$$

For the densities and heights involved in the model, the following results can be calculated based on the collected salinity and temperature pressures.

$$\begin{cases} \rho_i = f(S_i, T_i, P_i) \\ P_i = g \sum_{k=1}^{i} \rho_k \Delta H_k \\ \Delta H_k = C(fixed\ value) \\ \sum_{k=1}^{i} \Delta H_k = H_i \end{cases} \tag{17}$$

Similarly, It can derive the force on the submersible in the y direction as:

$$F_y = \frac{1}{2} a \sum_{i=1}^{n} \rho_i {v_{ayi}}^2 \Delta h_i \tag{18}$$

Force analysis of the model is obtained from Newton's second law as follows.

$$m \frac{d\vec{v}}{dt} = \vec{F} + \vec{F}_P + \vec{G} + \vec{F}_f \tag{19}$$

As it proceed with these analysis, it is worth noting that the gravity of the submersible is in equilibrium with the welfare of the submersible as shown by the conditions of the question.

$$\vec{F}_f = -\vec{G} \tag{20}$$

In the model it applied for the analysis, one factor that was not previously considered is mechanical failure. In the event of a mechanical failure in the submersible, it can adjust the power impact range $0\ 100\%$. Therefore, the final results of the calculations, taking this into account, are presented below:

$$\begin{cases} \frac{dv_x}{dt} = \frac{F_x}{m} \\ \frac{dv_y}{dt} = \frac{F_y}{m} \\ \frac{dv_z}{dt} = \frac{F_z}{m} \\ x = \int v_x dt \\ y = \int v_y dt \\ z = \int v_z dt \end{cases} \tag{21}$$

The calculations of the above model eventually lead to the following results: Figure 9

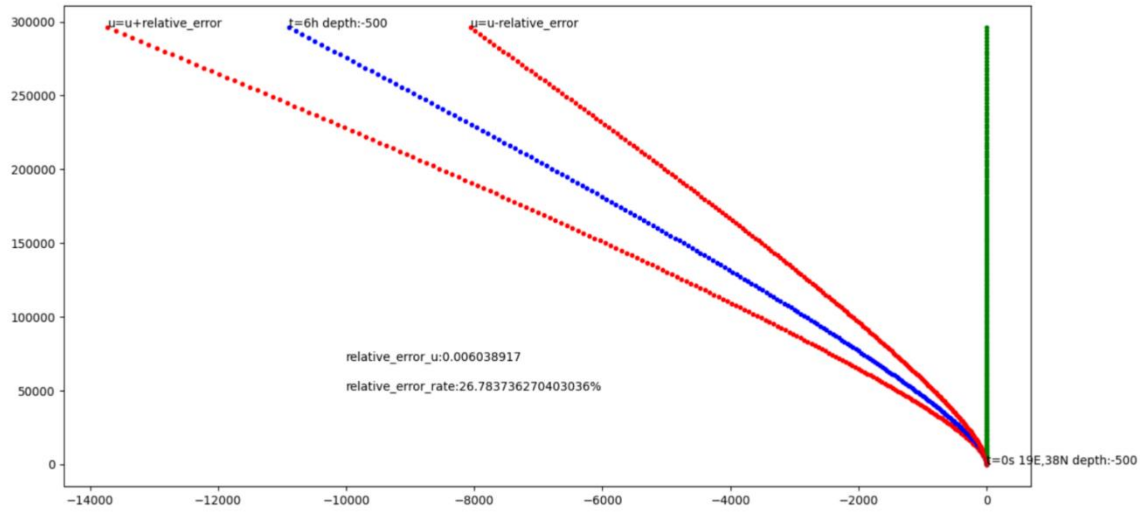

Figure 9. Uncertainty map

Then the uncertainty is 26.7837%. From the data, it can be seen that the model predicts better with smaller trajectory offsets.

4. Conclusions

In this work, POD decomposition is applied to process the data set, and the LSTM neural network is used to predict ocean currents, and it is applied to the actual scenario of finding a lost contact and losing power submarine. Finally, the ocean current prediction model and the position prediction model of the missing submarine are successfully established, and the error rate of the model is only 26.7837% by comparing the predicted results with the actual results.

Of course, the research method in this paper adopts POD decomposition to minimize the influence of some other factors. Such as the movement of human vessels, weather, and climate conditions, and the migration of large schools of fish on the seafloor. However, this can still lead to a high degree of inaccuracy in the forecast results. It may be possible to further improve the method in this regard in the future.

This study provides a research idea and framework to apply the neural network in machine learning to the field of ocean engineering to predict the change of ocean current and predict the position of the submarine. It proves the feasibility of applying the research method of machine learning to the field of ocean engineering.

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