Design of Sea Ice Monitoring UAV Platform Based on Machine Learning

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Abstract. Machine learning, as one of the most currently remarkably intelligent techniques, has achieved great success in many applications. It makes mechanical instruments and equipment become more automated. In order to realize the intelligent monitoring of polar glacier movement and environmental data, this paper designs a buoy platform that can be equipped with a small environmental monitoring UAV (Unmanned Aerial Vehicle) based on automated ice station technology. On the basis of the original environmental monitoring capabilities of the platform, the target structure is designed according to the needs of the landing of the UAV. Based on the SVM (Support Vector Machine) algorithm, the conditions are predicted whether to start the UAV according to the environment parameters around the platform, which reduce the risk of damage to the UAV due to wind and snow. The superiority of the SVM algorithm in UAV environmental recognition has been verified through field experiments.

1. Introduction

Sea ice is the product of the interaction between ocean heat flux and its surface heat budget, so the change of sea ice is an important factor affecting the environment [1-2]. At present, the international means to study the mechanism of the rapid change of arctic sea ice are relatively limited. Many countries have set up manned float-ice observation stations on sea-ice platforms to carry out manned long-term field observation. Various types of ice stations and buoy technologies have emerged. CALIB (Compact Air Launched Ice Beacon) buoys and IMB (The Ice Balance Buoy) sea ice mass balance buoys use data acquisition cards as the core, and realize the observation of sea ice temperature and thickness based on mounting various types of sensors [3-5]. In China 9th Arctic Scientific Expedition, the Arctic Sea-Ice-Gas Unmanned Ice Station Observation System was proposed for the first time with a structural framework of one subject and one letter mark. The unmanned ice station system has completed long-term data observation of sea ice in the same relative position. However, only part of the edge sea ice data was collected in the collection range and buoys such as CALIB and IMB. It is impossible to effectively observe the deeper areas of the Arctic Ocean.

In recent years, UAV technology has developed rapidly and has been applied to various fields through technological innovation. In polar sea ice observation, UAV have great application potential. In China 7th Arctic scientific expedition, DJI’s consumer-grade small UAV (DJI phantom4) was used to successfully obtain some sea ice images, and the analysis of the coverage of the molten
pool and the roughness of the ice surface was completed [6]. In order to achieve the purpose of unattended, this study designed a marine buoy platform for research and utilization of small UAV. This can provide a UAV landing bay for charging and protection. Through the collection of environmental data, the classifier is continuously trained to ensure that the UAV is released when the surrounding environment is safe based on SVM. At the same time, the platform and the UAV are used to obtain data on the ice layer, the sub-ice environment, and the sea ice and atmospheric environment around the buoy platform.

2. System hardware design

The overall system includes two parts: platform cabin control and buoy environment monitoring and two subsystems of data acquisition system and control and system. The structure diagram is shown in Figure 1. In the environmental monitoring part, the water and underwater sonar collects the distance from the ice and snow to monitor the change of sea ice thickness, and the temperature field data monitors the temperature change to correct the sea ice change data. The data set that can meet the cruising conditions of the UAV is constantly being improved, through the collection of images and atmospheric environment data. The cabin control part includes this control system and communication system. The control system is responsible for controlling the opening of the hatch, the release of the UAV platform and the analysis of attitude and environmental data. The communication system is divided into two parts. At the scene, the communication system completes the transmission of the UAV’s take-off and about to return instructions and UAV attitude information based on WLAN technology and TCP/IP protocol. In the long-distance, the Iridium satellite network transmits data to the data interface of the laboratory and can debug remotely under emergency conditions.

![Figure 1. The overall framework of the system](image)

It mainly uses aluminum alloy, fiber reinforced plastics, PE floating material, and stainless steel as the main constituent materials. The structure of the UAV is carbon fiber materials. Taking into account that in the Arctic environment, if unattended for a long time, ice and snow will accumulate and cover the surface of the cabin, so the hatch cover is designed as a hemispherical shape. Four hydraulic supports are used to control the hatch cover opening. The parameters of each part are shown in Table 1.

| Characteristics                  | Value(mm) |
|----------------------------------|-----------|
| Dome diameter                    | 1800      |
| Dome thickness                   | 4         |
| Lifting bracket length           | 1000      |
| Lifting bracket width            | 300       |
| Minimum height of lifting bracket| 160       |
| Vertical movement distance of    | 1100      |
| lifting bracket                  |           |
The structure of the platform is shown in Figure 2. The UAV is placed in the middle of the platform and it is fixed by a fixing buckle. When the drone is released, the fixing buckle opens. The control circuit and power supply are placed in the buoyant material. The function of the buoyancy material is to provide buoyancy for the platform when it floats out of the sea ice range. This method can ensure that it floats in the sea. Vertical platform motor and hydraulic support provide power for platform movement.

3. Protection decision based on SVM
In the Arctic Ocean environment, there are many bad weathers such as wind and snow. If the UAV is released for sea ice monitoring in this situation, the system cannot run normally. Even the drone is damaged causing serious damage. In the wild environment, a lot of experiments have been conducted on whether the UAV was able to operate normally. We record environmental data of wind speed, humidity, air pressure and temperature data during the UAV cruising, and divide the data into two categories. It can be recorded as y=1 for normal cruise flight, and can be recorded as y=-1 for normal cruise flight. Environment parameter vector e = (s, h, p, t), where s is the wind speed unit m/s, h is relative humidity, p is air pressure unit KPa, t is temperature unit ℃.

Define the training sample set as
\[ D = \{(e_1, y_1), (e_2, y_2), ..., (e_l, y_l)\} \]
\[ y_i = \{-1, +1\} \]

The general form of the linear classification hyperplane [7] equation can be written as
\[ w^T e + b = 0 \]

Where w is the hyperplane normal vector, which determines the direction of the hyperplane. b is the offset, which determines the distance between the hyperplane and the origin. Divide the data into \( w \cdot e > 0 \), \( w \cdot e < 0 \), two types of points. This can be equivalent to
\[ y_i (w \cdot e_i) \geq 1; (i = 1, 2, ..., l) \]
\[ y_i (w \cdot e_i) \leq -1; (i = 1, 2, ..., l) \]

Introduce relaxation variables \( \xi_i \geq 0 \) (Describe the size of the deviation from the sensitive area) and Penalty constant \( C > 0 \) (C has a positive correlation with the model's complexity) for each sample point \((y_i, e_i)\). Eventually, the problem can be described as an optimal problem [8]
\[
\begin{align*}
\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{l} \xi_i \\
\text{s.t. } y_i (w \cdot e_i + b) \geq 1 - \xi_i \\
\xi_i \geq 0, (i = 1, 2, ..., l)
\end{align*}
\]

Use the Lagrange multiplier method to solve the most problematic
4. Performance Evaluation of the Platform

Evaluate the performance and stability of the system to ensure long-term operation of the system unattended. Four performance indicators are quantified, precision (PRE), recall rate (Recall), F1 Score and accuracy rate (ACC). The platform is placed outdoors for on-site experimental testing.

\[
\text{PRE} = \frac{TP}{TP + FP} \\
\text{TPR} = \frac{TP}{TP + FN} \\
F1 = \frac{2 \times \text{PRE} \times \text{TPR}}{\text{PRE} + \text{TPR}} \\
\text{ACC} = \frac{(TP + TN)}{(TP + TN + FP + FN)}
\]

Where TP is the number of samples that it can cruise normally under actual conditions and be same as forecast result. TN is the number of samples that it cannot cruise normally under actual conditions and be same as forecast result. FN is the number of samples that it can cruise normally under actual conditions and be different from forecast result. FP is the number of samples that it cannot cruise normally under actual conditions and be different from forecast result. PRE is to predict the proportion of correct samples to all samples in normal cruise samples. The recall rate is also called TPR (true positive rate), which represents the proportion of samples predicted correctly to be able to cruise normally in all samples with correct prediction results. F1 Score is a comprehensive score of PRE and TPR. Accuracy of ACC response classifier.

Experiment comparing SVM model with GBDT (Gradient Boosting Decision Tree) model [9]. Two identical hardware structures were manufactured by Taiyuan University of Technology. They were written different programs, SVM and GBDT, and tested in Taiyuan. The predicted results are verified on the testing set. The results are shown in Table 2. It can be seen that the accuracy rate of GBDT model is low, only 73.33%. This indicates that the GBDT model has a weak ability to mine hidden information in the data, which cannot accurately reflect the characteristics of decision-making under manual operation. The accuracy of SVM model is as high as 86.67%, and its F1 score is much higher than GBDT model. This shows that the prediction results of SVM model are more similar to the actual situation.
Table 2. Quantitative indicators of different models

| Decision model | SVM  | GBDT |
|----------------|------|------|
| PRE            | 90.23% | 84.03% |
| TPR            | 94.49% | 82.64% |
| F1 Score       | 92.31% | 83.33% |
| ACC            | 86.67% | 73.33% |

At the same time, the number of UAV daily cruises of different models is also recorded. The program is set to work once every two hours (12 times one day). The statistical results are shown in the figure 4.

On the 10th and 35th days of the experiment, the number of cruises decreased, and extreme weather may have occurred. Both models can avoid risks and do not cruise, and the number of cruises is close to one day. Except for extreme weather, SVM model is significantly better than the GBDT model. One or two more cruises and glaciers can be photographed daily.

5. Conclusion

Aiming at the problem of effective observation of sea ice in the deeper regions of the Arctic Ocean by the North, this paper designs a UAV buoy platform based on mature buoy and UAV technology. It is proposed to use the support vector machine classifier to distinguish and identify the surrounding environment of the platform, giving the most secure control flow. This method can learn samples of environmental parameters, and it can continuously optimize the flightable cruising conditions to ensure longer and effective sea ice observations by UAV on the platform.

The experimental results of the field flight environment show that the prediction method proposed in this paper. The method can distinguish the typical parameters of the UAV cruise environment characteristics, and then achieve the purpose of protecting the UAV. In the case of unattended operation, the feasibility of long-term safe and reliable operation of the system is ensured.

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