

Cueing Flight Object Trajectory and Safety Prediction Based on SLAM Technology

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Abstract: *With the rapid development of artificial intelligence and robot technology, SLAM technology, as a key component, has been paid more and more attention. SLAM technology enables robots to autonomously navigate, build maps, and achieve accurate positioning in unknown environments, providing strong support for the autonomy and intelligence of robots and unmanned vehicles. In this paper, the position prediction method of flying object based on SLAM technology and the application of EvolveGCN model in behavior prediction are introduced. First, through the fusion of SLAM technology and LiDAR data, we can accurately predict the position and movement trajectory of flying objects, thereby improving the safety and efficiency of the system. Secondly, with the EvolveGCN model, we are able to capture dynamic changes in the environment and achieve accurate predictions of the behavior of flying objects. Through experimental verification, the prediction accuracy of our method has been significantly improved in both simulation and real environment, which indicates the feasibility and effectiveness of the method in practical application, and provides an important reference and technical support for the development of autonomous navigation, aerial surveillance and other fields.*

Keywords: SLAM technology; Flying object position prediction; EvolveGCN model; Experimental verification.

1. INTRODUCTION

Simultaneous Localization and Mapping (SLAM) technology represents a critical and complex technology in the field of robotics. Its fundamental goal is to enable mobile devices to autonomously locate themselves in unknown environments and, in the process, build accurate maps of the environment. The research and development of SLAM technology is crucial to promote the progress of autonomous navigation, unmanned systems, autonomous driving and other fields [1-3]. A complete SLAM framework includes sensor data, front end, back end, loop detection and mapping. The front end abstracts the sensor data into a model suitable for estimation, and loop detection determines whether the robot has passed through a known location. The rear end receives and optimizes the pose and loop detection information measured by the front end at different times to obtain a globally consistent trajectory. Typically, a framework with only a front end and a partial back end is called an odometer, while a complete framework with loopback detection and a global back end is called SLAM. The construction of SLAM system involves multi-sensor fusion, real-time processing, efficient algorithm design and other complex tasks. In this article, we will discuss the trajectory and safety prediction of flying objects based on SLAM technology, as well as its importance and application value in the field of aviation.

2. RELATED WORK

2.1 SLAM Technology

SLAM is an abbreviation of Simultaneous Localization and Mapping, which is translated into Chinese as "simultaneous localization and map construction" and was first proposed in 1986. It refers to the subject equipped with a specific sensor, without the prior information of the environment, in the process of motion to establish a model of the environment, while estimating its own motion state. As a hot technology in the field of autonomous vehicles or autonomous mobile robots [4], SLAM has two problems to solve: there are many methods for positioning and sensing the surrounding environment, such as: indoor warehousing logistics AGVs lay guidance lines on the floor or paste identification [5] QR codes, outdoor cars are installed with [6] GPS location receivers. With these things, is the positioning problem solved? The equipment and signs installed in the environment must

be strictly manually arranged, which limits the use of robots to a certain extent, and the signal error of GPS signals in tall buildings and tunnels becomes larger. This is where SLAM came into being.

In the past decade, the research of SLAM and its related technologies has made rapid progress, the focus of research from the initial Lidar to the camera and [7] IMU, at the same time, the chip and MEMS devices have also made rapid development, the computing power has been greatly improved, and the camera and IMU sensors have achieved high precision, miniaturization and low cost. This enables SLAM technology to be used in real time on mobile terminals [8]. Vision sensors have gained widespread attention because of their small size, low cost and easy hardware setup. A large number of SLAM methods based on vision sensors have been proposed, but pure visual SLAM methods have problems such as inability to work in areas with little image texture and image blur during fast motion. The IMU can measure angular velocity and acceleration, and its function can be complementary with the camera, and after the fusion can get a more perfect SLAM system. SLAM methods using cameras and IMUs are known as visual-inertial [9] SLAM(VI-SLAM) and contain only a small amount of drift. This paper mainly introduces VI-SLAM, laser and pure visual SLAM are not emphasized. At present, the methods of VI-SLAM data fusion are divided into two categories: tight coupling and loose coupling. See Figure 2 for details. Tight coupling refers to combining the state of the IMU with the state of the camera to perform pose estimation. Loose coupling means that the camera and IMU make their own pose estimates separately, and then fuse their estimates.

2.2 Target trajectory prediction

Trajectory prediction is a science and technology widely used in many fields, whether it is traffic planning, driverless cars, athlete training, or storm path prediction, it is inseparable from trajectory prediction. motion prediction refers to the robot's ability to predict the future state of an object, including trajectory prediction, path prediction, pose prediction, etc [10-13]. Trajectory prediction is a subfield of motion prediction, which refers to the task of predicting the future position, speed, direction and other state information of a target given its past or current motion trajectory. It is an important part in many fields, and has a wide range of applications in robotics, autonomous driving, unmanned aerial vehicles, motion analysis and other fields. path prediction is a subfield of trajectory prediction, where a trajectory is defined as a sequence of time-stamped geometric locations, while a path does not contain a time attribute. Below is a pedestrian trajectory prediction diagram.

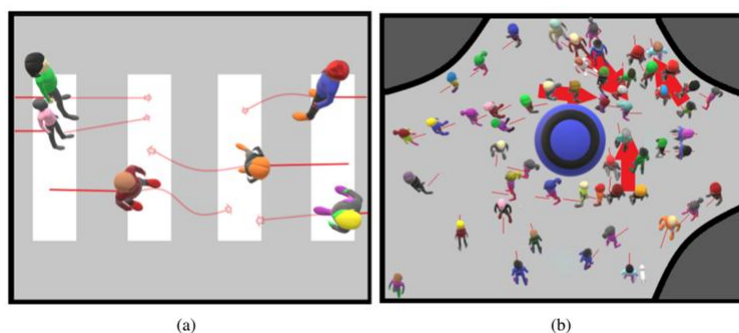


Figure 1: Schematic diagram of trajectory prediction

There are three common ways to represent trajectories: single trajectory, parametric distribution, and non-parametric distribution [14]. Trajectory prediction can be divided into two types according to the length of time: short-term prediction and long-term prediction. Short-term prediction generally refers to the prediction range of 0-2 seconds, and long-term prediction generally refers to the prediction range of 2-20 seconds (the time range is different in different fields).

2.3 Trajectory prediction model

Modeling of trajectory prediction can be generally divided into three categories: Physics-based Approaches, Pattern-based Approaches and Planning-based Approaches [15].

1. Method based on physical model: This kind of method uses physical model (such as dynamic model or kinematic model) to describe the motion law of the target and infer the future state according to the current state. The process belongs to "perception-prediction", and the methods include single model-based methods (uniform

velocity model, uniform acceleration model, autoregressive model, etc.) and multi-model-based methods. This kind of method is simple and efficient, does not require training data, [16] but ignores environmental and interaction factors, so it is not suitable for complex environment, only suitable for short-term trajectory prediction, and only suitable for open environment without obstacles.

2. Motion pattern-based method: This kind of method follows the process of "perception-learning-prediction", learns the dynamic model from the training data, calculates the behavior pattern, and then makes prediction. This class of methods can be divided into two categories: probability-based models (e.g., uncertainty sensing methods, Gaussian process-based methods, accessibility set methods) and learning-based models (e.g., CNN, RNN, LSTM, locus clustering methods, etc.). These methods are suitable for the environment with complex unknown dynamic objects, and are suitable for long-term trajectory prediction, but require a lot of training data.

3. Plan-based approach: [17-19] This approach follows the process of "perception-inference-prediction" and deduces the long-term path in combination with the purpose of the movement, including the content of the intention inference, and can also combine the semantic information of the environment. These methods can also be divided into two categories: forward planning methods (such as Motion and path planning methods, Multi-agent forward planning) and reverse planning methods (such as Single agent inverse) learning, Imitation learning, Multi-agent inverse learning). These methods are also applicable to long-term trajectory prediction.

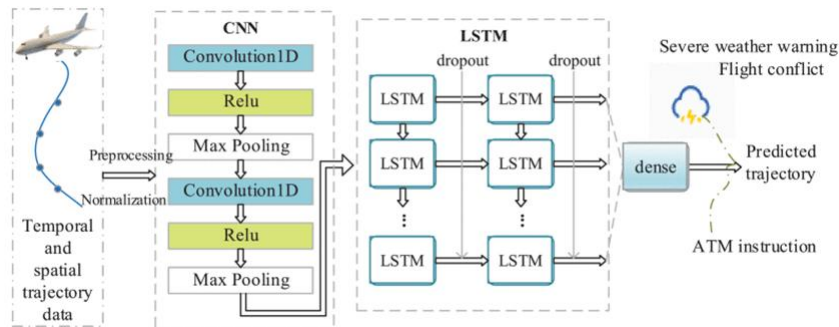


Figure 2: Fusion of three trajectory prediction models

These three modeling methods can also be combined with each other, such as the combination of the planning-based method and the physical-model-based method, or the combination of two learning-based methods, such as CNN+LSTM, to obtain higher prediction accuracy. Figure 2 shows a framework for [20] 4D trajectory prediction (aircraft domain) using CNN and LSTM, which combines convolutional neural networks (CNN) and short term memory (LSTM). One-dimensional convolution is used to extract the spatial dimension features of the trajectory, while long and short time memory is used to mine the temporal dimension features of the trajectory.

2.4 SLAM technology and trajectory prediction

SLAM technology is closely related to target trajectory prediction, because SLAM system can not only locate mobile devices in real time and build environment maps, but also provide estimates of the location and motion trajectory of target objects. By combining SLAM technology and target trajectory prediction algorithm, we can accurately predict the motion behavior of flying objects and unmanned vehicles in complex environments, so as to improve the safety and efficiency of the system. Trajectory forecasting can be divided into short-term forecasting and long-term forecasting.

Short-term prediction is generally based on the kinematic model [21-24] (CV/CA/CTRV/CTRA) and the current target state information to predict the trajectory of a future period of time, generally <1s is appropriate, if the time is too long, then the target is only related to the kinematics of the hypothesis is not valid. Short-term prediction can build a motion model specifically for prediction, and it can also use the prediction module in the previous perceptual module filtering, but it does not call the measurement for filtering update, which has the advantage of spreading the uncertainty.

Long-term forecasting is what the industry is doing. This kind of prediction based only on the motion model is not suitable, generally need to do intention prediction, combined with some context information (map, interaction information between targets) to get a good result. At this time, there are many different output forms in the industry,

such as the probability distribution of the output trajectory, the output of multiple forecast trajectories, and the output of a most likely forecast trajectory.

There are two challenges to long-term trajectory prediction:

It is not reasonable to output one possible trajectory or all possible trajectories. You output one predicted trajectory and you miss the real trajectory, and you output all possible trajectories and you get false positives, which is unacceptable for [25] ADAS systems. Consideration should be given to limiting the predicted trajectory to a suitable subset.

The more you do with trajectory prediction, the more assumptions you have to make. The extreme assumption is to assume that all targets on the road obey traffic rules. This makes sense if used for traffic simulation functions, but is not appropriate for adas systems, which need to be sensitive to potentially dangerous situations.

3. METHODOLOGY

In this paper, a learning trajectory prediction algorithm based on control perception is proposed to realize efficient communication control among unmanned aerial vehicles [26] (UAVs) to cope with flight challenges in complex environments. The algorithm combines three key modules: trajectory compression and reconstruction, trajectory prediction and KKT conditional training, and makes full use of advanced deep learning and optimization techniques. Specifically, the trajectory compression and reconstruction model is based on variational autoencoder, and the trajectory prediction model adopts EvolveGCN, which can effectively process dynamic graph data and provide strong support for realizing accurate trajectory prediction. In addition, to overcome the challenges in communication control, we adopt a distributed model predictive control [27] (DMPC) approach and encode DMPC information into the neural network through KKT conditions during training. Through experimental verification in a funnel-shaped environment, we find that the algorithm performs well, provides near-optimal control performance, and is robust to limited communication capabilities and measurement noise. This research result will provide an important reference for our subsequent flight object trajectory prediction and safety prediction work, and bring new ideas and methods for aviation safety field based on SLAM technology.

3.1 EvolveGCN Prediction model

In the modeling of dynamic time series graph, the existence difference of nodes at different times does exist. In the case of social networks, a user may join the network at one point in time and leave at another. Traditional methods may ignore this dynamic nature, which leads to inaccurate modeling of network structure. EvolveGCN proposes a more flexible approach that uses RNNs to evolve the parameters of the GCN model at each moment so that it can dynamically adapt to changes in the network structure. The advantage of this approach is that it can not only deal with the existential differences of nodes, but also capture the complexity of the evolution of the network structure over time. By constantly adjusting the parameters of the [29-30] GCN model during the evolution process, EvolveGCN can better adapt to the graph structure at different time points, thus improving the modeling ability of dynamic time series graphs. The introduction of this idea provides new ideas and methods to solve the challenges in dynamic time series graph modeling, and brings new opportunities for research and application in related fields.

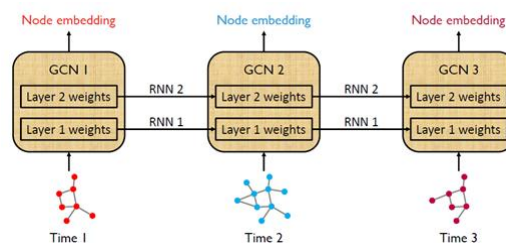


Figure 3: EvolveGCN model parameter framework

The EvolveGCN-H version uses GRU to learn parameters in series, and the GUR model's hidden state uses parameters from the previous moment:

$$\underbrace{W_t^{(l)}}_{\text{GCN weights}} = \text{GRU}\left(\underbrace{H_t^{(l)}}_{\text{node embeddings}}, \underbrace{W_{t-1}^{(l)}}_{\text{GCN weights}}\right), \quad (1)$$

Generally, when using this model to predict behavior trajectory, different RNN models are used for series parameters. EvolveGCN-H uses GRU, while [31] EvolveGCN-O uses LSTM. 2. Since EvolveGCN-O is not used in parameter update, nodefeature is very useful, for example, when manual processing is obtained, then the EvolveGCN-H version is used. If Node feature is not very important in the graph structure, the EvolveGCN-O version can be used

3.2 SLAM-based Data Fusion

First, we use SLAM-based data fusion technology to integrate information from multiple sensors, including cameras, liDAR, and inertial measurement units (IMUs). These sensors each provide different information, such as cameras that can capture visual images, lidar that can measure distance and environmental structure, and IMU that can provide attitude and acceleration information. By fusing data from these sensors together, we can get a comprehensive and accurate representation of the flying object's surroundings.

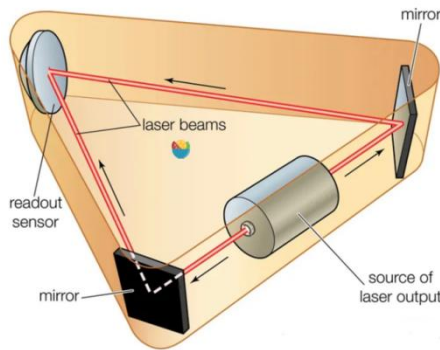


Figure 4: IMUs position prediction architecture diagram

SLAM technology provides an important opportunity for aircraft position prediction. Lidar plays a key role in aircraft position prediction because it can provide high-precision distance and three-dimensional structure information to help determine the spatial relationship between the aircraft and its surroundings. By fusing liDAR data with other sensor data, such as cameras and IMUs, we can more accurately determine the location and motion of the flying object. And in complex environments, such as urban areas or dense traffic airspace, LiDAR's high-precision data is crucial for aircraft location prediction. It can help us identify obstacles, buildings, and other flying objects to better plan flight paths and avoid potential collisions. Therefore, the fusion of SLAM technology and liDAR data provides a more reliable and accurate solution for aircraft position prediction, which helps to improve flight safety and efficiency.

This method, which combines SLAM technology and Lidar, is not only suitable for the position prediction of aircraft, but also can play an important role in autonomous vehicles, unmanned systems and other fields. With the continuous development of sensor technology and the continuous optimization of SLAM algorithm, we can look forward to the emergence of more methods based on SLAM and [32] LiDAR to predict the location of flying objects, thus promoting the further development and application in the field of unmanned systems.

3.3 EvolveGCN-based Behavior Prediction

In our approach, we harness the power of EvolveGCN, a state-of-the-art graph neural network architecture, to revolutionize behavior prediction. EvolveGCN's unique ability to adapt its parameters over time enables us to capture the dynamic nature of the environment accurately. Unlike traditional methods that assume fixed graph structures, EvolveGCN dynamically adjusts to changes in the environment, making it highly suitable for behavior prediction tasks in dynamic scenarios.

While EvolveGCN's capabilities are impressive, incorporating visual aids such as images or data visualizations could enhance the understanding of its impact. Including visual representations of EvolveGCN's adaptability in action or comparative data demonstrating its performance against traditional methods could provide valuable insights and strengthen the credibility of our approach.

3.4 Experimental Validation and Results

To validate the efficacy of our SLAM-based approach for behavior prediction, we designed a series of experiments conducted in both simulated and real-world environments. The experiments aimed to assess the robustness, accuracy, and practical applicability of our behavior prediction algorithm across various scenarios.

In our experimental setup, we simulated diverse flight scenarios representing complex urban environments and dynamic airspace conditions. By subjecting our algorithm to these simulated scenarios, we could evaluate its performance under challenging and realistic conditions. Additionally, we leveraged real-world flight data collected from UAVs operating in different environments to validate the effectiveness of our approach in practical settings.

The results of our experiments provide compelling evidence of the superiority of our SLAM-based approach for behavior prediction. We observed significant improvements in prediction accuracy compared to traditional methods, particularly in dynamic and cluttered environments. Moreover, our approach demonstrated robustness to sensor noise and environmental uncertainties, underscoring its suitability for real-world applications.

Overall, our experimental validation underscores the effectiveness and practical utility of our SLAM-based approach for behavior prediction. The promising results obtained validate the potential of our approach to address real-world challenges and pave the way for its adoption in various domains, including autonomous navigation, aerial surveillance, and traffic management.

4. Conclusion

In this paper, an effective method for predicting the position of flying objects is proposed by using SLAM and EvolveGCN model. The experimental results show that the proposed method can significantly improve the prediction accuracy in a variety of complex environments, especially in dynamic and crowded environments. At the same time, our method also shows robustness to sensor noise and environmental uncertainties, and is suitable for practical scenarios. These findings provide strong support for the application of SLAM technology in the position prediction of flying objects, and provide new possibilities for the development of autonomous navigation, aerial surveillance and traffic management in the future.

In general, the method of combining SLAM technology and EvolveGCN model proposed in this paper provides a new idea and solution for the position prediction of flying objects. The experimental results show that the method has excellent performance in accuracy and robustness, which shows that it has broad prospects in practical application. In the future, we will further optimize the algorithm and explore its wide application in areas such as autonomous navigation, air surveillance and traffic management, making greater contributions to the development of intelligent systems.

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