應用多模態深度學習於對流胞路徑預測與追蹤

Prediction and Tracking for Paths of Convective Cells Based on Multimodal Deep Learning

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摘　要

對流胞路徑追蹤為路徑預測之重要前置步驟，正確路徑追蹤能使路徑預測更加準確，目前於台灣中央氣象局對流胞現行追蹤方式來自美國國家劇烈風暴實驗室(National Severe Storm Laboratory,NSSL)之WDSS系統中使用對流胞辨識和路徑追蹤演算法(Storm Cell Identification and Tracking algorithm, SCIT) (Johnson et al., 1998)，此方式於對流胞密集度較鬆散的情形下有良好的追蹤效果，但相對於較密集的情形時仍有改善空間，基於機器學習與深度學習於氣象領域已有良好的表現，其中雷達回波在結合卷積結構和遞迴結構的神經網路模型(例:ConvLSTM)於降雨預報、雷達回波預測等方面有不錯的發展，且近期無使用機器學習與深度學習方式應用於對流胞追蹤，因此本研究提出使用對流胞的數值模態資料與雷達回波圖像模態利用多模態進行結合，預測對流胞下一刻移動位置，並比對下一刻所有對流胞中位置與預測結果最相近者為此對流胞下一刻路徑進行追蹤。

本研究針對模型單任務與多任務、資料集之一般與差分表示方式、單模態與不同多模態融合方式、最佳模型應用於路經追蹤，四個方面進行實驗，實驗結果如下:

1. 於數值資料單模態LSTM模型之輸出入於一般方式和差分方式預測結果比較:
   由於差分為輸入特徵變化量，再經由前一刻特徵做修正，實驗結果優於直接預測對流胞下一刻之特徵。
2. 於差分數值資料中單任務與多任務模型LSTM預測結果:
   在所有特徵中(經度、緯度)，台灣周遭的對流胞較多以東西向移動，經度變化較大，緯度變化較小，以單任務方式做預測結果優於多任務方式。
3. 單模態與不同融合方式之多模態預測結果比較:
   以對流胞經緯度結果說明，單模態LSTM及ConvLSTM經緯度直線距離(KM)預測誤差分別為4.8598及5.1851，多模態中特徵融合及決策融合預測誤差分別為1.1722及1.0841，結果說明結合數值及雷達回波圖像之多模態模型優於所有單模態模型，其中又以決策融合方式為最佳。
4. 挑選對流胞較密集之時間利用上述實驗中最佳路徑預測模型進行路徑追蹤結果並與SCIT比較:
5. 個案挑選2021年10月10日、10月14日、10月23日之追蹤結果視覺化及路經追蹤正確率皆為利用多模態決策融合模型為最佳，優於氣象局現有追蹤方式SCIT、單模態LSTM模型。

關鍵字：深度學習、對流胞、路徑追蹤、路徑預測、雷達回波、特徵融合、決策融合、多模態融合、單模態、時間序列

Abstract

The goal of this research is to establish an AI real-time autumn weather typing system in Taiwan, which can automatically identify daily weather types based on 5 synoptic features. The main work can be divided into two parts: diagnostic analysis of autumn weather types and establishment of AI automatic recognition module. From the data analysis, the 5 clusters are: a cyclonic circulation or TC covering Taiwan (TC type), northeasterly wind near northern Taiwan (NE type), a TC-like circulation in the South China Sea accompanied northeasterly wind near northern Taiwan (TC-NE type), weak easterly wind (E type), and weak northly wind (N type). The AI module is developed based on Auto-Encoder and K-means, and tested by the 5 weather types above. The results show that if the weather type is directly compared by similarity, the error rate of the module is high. This may be related to the fact that similarity comparison cannot simultaneously handle intra-group distance and inter-group distance. From the experiments using given centroids and selected training members by K-means, it is shown that the accuracy of the AI real-time autumn weather typing system in Taiwan can reach 75%, and related results will be discussed in the paper. Cell tracking of convective cells is an important preliminary step in path prediction. Accurate cell tracking enhances the accuracy of path prediction. Currently, the Taiwan Central Weather Bureau adopts the Storm Cell Identification and Tracking algorithm (SCIT) from the National Severe Storm Laboratory's WDSS system (Johnson et al.,1998) for convective cell tracking. While this method performs well in scenarios with loosely clustered convective cells, there is room for improvement in denser scenarios. Machine learning and deep learning have shown promising results in meteorology, particularly in rainfall prediction and radar echo forecasting using neural network models that combine convolutional and recurrent structures, such as ConvLSTM. However, there has been no recent application of machine learning and deep learning techniques in convective cell tracking. Therefore, this study proposes a multimodal approach that combines numerical modal data of convective cells with radar echo image modalities. The aim is to predict the next movement position of a convective cell and track its path by comparing the predicted position with the closest match among all convective cells in the subsequent moment.

This study conducted experiments on four aspects: model single-task and multi-task learning, general and differential representation of datasets, single-modality and different multimodal fusion approaches, and the application of the optimal model in cell tracking. The experimental results are as follows:

1. Comparison of the predictions between general and differential representation in a single-modality LSTM model using numerical data:
   The experimental results showed that the differential representation, which captures the changes in input features and corrects them based on the previous moment's features, outperformed the direct prediction of the next moment's convective cell features.

2. Prediction results of single-task and multi-task LSTM models using differential numerical data:

Among all the features (longitude, latitude), convective cells around Taiwan tend to move in the east-west direction, with larger variations in longitude and smaller variations in latitude. The prediction results using the single-task approach outperformed the multi-task approach.

3. Comparison of prediction results between single-modality and different fusion approaches in multimodal predictions:
   Taking convective cell longitude and latitude as examples, the prediction errors (in terms of straight-line distance in kilometers) for single-modality LSTM and ConvLSTM models were 4.8598 and 5.1851, respectively. In the multimodal approach, the prediction errors for feature fusion and decision fusion were 1.1722 and 1.0841, respectively. These results indicate that the multimodal model combining numerical and radar echo image data outperformed all the single-modality models, with the decision fusion approach being the most effective.

4. cell tracking results using the optimal path prediction model on time intervals with denser convective cells compared to SCIT:
   For the selected cases on October 10th, October 14th, and October 23rd, the visualization of the tracking results and the accuracy of cell tracking were both highest using the multimodal decision fusion model. This model outperformed the existing tracking method SCIT and the single-modality LSTM model.

Key word: deep learning, convective cells, cell tracking, path prediction, radar echo, feature fusion, decision fusion, multimodal fusion, single-modality, time series.