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A Review of Typhoon Detection, Tracking and Intensity Estimation Using Deep Learning and Multi-modal Remote Sensing Data

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Abstract. Typhoons rank among the most destructive natural disasters globally, inflicting substantial casualties and enormous economic losses across the world each year. Accurate typhoon detection, tracking, and intensity estimation are crucial for disaster warning and risk management. Traditional typhoon monitoring methods primarily rely on numerical weather prediction models and expert judgment, which suffer from limited accuracy and insufficient timeliness. In recent years, the rapid development of deep learning technologies has brought new opportunities to typhoon research, particularly demonstrating significant advantages in multi-modal remote sensing data fusion and automated feature extraction. This paper systematically reviews the current state of typhoon detection, tracking, and intensity estimation technologies based on deep learning, analyzes the application of multi-modal remote sensing data in typhoon monitoring, discusses current technical challenges, and prospects future development trends. Research indicates that deep learning methods show superior performance in automated typhoon feature recognition, temporal sequence modeling, and multi-source data fusion, providing new technical pathways for improving typhoon forecasting accuracy and operational efficiency.

Keywords: Typhoon detection, Deep learning, Multi-modal remote sensing, Intensity estimation, Tracking algorithm

1. Introduction

Typhoons, as intense tropical cyclones occurring in the Western Pacific, pose severe threats to coastal regions and maritime activities. These weather systems are characterized by extremely strong winds, heavy precipitation, and complex three-dimensional structures including the eye, eyewall, and spiral rainbands [1]. The formation and evolution of typhoons involve complex atmospheric dynamics, making accurate prediction and monitoring challenging yet essential for disaster preparedness and mitigation.

Traditional typhoon analysis has relied heavily on numerical weather prediction models, statistical methods, and subjective interpretation techniques such as the Dvorak method [2]. While these approaches have provided valuable insights, they often suffer from limitations including computational constraints, subjective bias, and insufficient utilization of the increasing volume of

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satellite observations [3]. The emergence of deep learning technologies, combined with the proliferation of multi-modal remote sensing data, offers unprecedented opportunities to enhance typhoon monitoring capabilities [4].

Recent advances in satellite technology have provided access to high-resolution, multi-temporal observations from various sensors including visible/infrared imagers, microwave radiometers, and scatterometers . The integration of these diverse data sources through sophisticated deep learning frameworks enables more comprehensive understanding of typhoon characteristics and behavior. This technological evolution has sparked significant interest in developing automated, objective, and accurate methods for typhoon detection, tracking, and intensity estimation [5].

Research theme and questions—This review examines how deep learning combined with multimodal satellite data supports three operational tasks: (1) detection and structural delineation, (2) tracking/nowcasting, and (3) intensity estimation.

2. Multi-modal remote sensing data for typhoon monitoring

2.1. Satellite-based observations

Modern typhoon monitoring relies extensively on satellite-based remote sensing systems that provide continuous, global coverage of atmospheric conditions. Geostationary satellites such as Himawari-8/9, GOES-16/17, and Fengyun-4 series offer high temporal resolution observations (typically 10-15 minutes) that are crucial for tracking rapidly evolving typhoon systems [6]. These satellites carry advanced imaging instruments capable of capturing data across multiple spectral channels, from visible light to thermal infrared wavelengths.

The Advanced Baseline Imager (ABI) on GOES-16/17 and the Advanced Himawari Imager (AHI) on Himawari-8/9 represent significant technological advances, providing 16 spectral channels with spatial resolutions ranging from 0.5 to 2 kilometers [7]. These high-resolution observational data enable detailed analysis of typhoon structures, encompassing key features such as eyewall dynamics, convective patterns, and cloud-top characteristics—all of which are critical for accurate typhoon intensity assessment.

Polar-orbiting satellites complement geostationary observations by providing higher spatial resolution data and access to additional spectral regions. The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard Terra and Aqua satellites offers detailed visible and infrared imagery [8], while the Visible Infrared Imaging Radiometer Suite (VIIRS) on Suomi NPP and NOAA-20 provides enhanced low-light imaging capabilities for nighttime typhoon monitoring .

2.2. Microwave remote sensing

Microwave sensors play a crucial role in typhoon observation due to their ability to penetrate clouds and provide information about precipitation, atmospheric temperature and humidity profiles, and ocean surface conditions. The Advanced Microwave Scanning Radiometer 2 (AMSR2) aboard GCOM-W1 provides valuable data on sea surface temperature, precipitation rates, and atmospheric water vapor content [9].

Scatterometer data, derived from instruments such as the Advanced Scatterometer (ASCAT) and Oceansat Scatterometer (OSCAT), enables direct measurements of ocean surface wind vectors—information that is indispensable for precise typhoon analysis. These measurements complement model-derived wind fields and provide ground truth for validation of intensity estimates derived from other sensors.

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The Global Precipitation Measurement (GPM) mission, successor to the Tropical Rainfall Measuring Mission (TRMM), provides critical precipitation observations through its dual-frequency precipitation radar and multichannel microwave radiometer [10]. These observations are particularly valuable for understanding typhoon structure and intensity changes, as precipitation patterns are closely linked to storm dynamics.

3. Deep learning approaches for typhoon detection

3.1. Convolutional Neural Networks for feature extraction

Convolutional Neural Networks (CNNs) have emerged as the dominant approach for automated typhoon detection from satellite imagery. Unlike traditional methods that rely on hand-crafted features and threshold-based algorithms, CNNs can automatically learn hierarchical representations of typhoon characteristics directly from raw satellite data.

Early applications of CNNs to typhoon detection adapted existing computer vision architectures such as AlexNet, VGG, and ResNet [11]. These networks demonstrated superior performance compared to traditional methods in identifying typhoon presence and location within satellite images. The ability of CNNs to capture multi-scale features makes them particularly well-suited for typhoon analysis, as these systems exhibit characteristic patterns across different spatial scales.

More recent developments have focused on designing specialized CNN architectures optimized for meteorological applications [12]. These custom networks often incorporate domain knowledge about typhoon structure and behavior, leading to improved detection accuracy and reduced false positive rates. Attention mechanisms have been integrated into CNN architectures to focus on the most relevant regions of satellite imagery, such as the typhoon eye and spiral rainbands.

3.2. Object detection frameworks

The evolution of object detection frameworks has provided powerful tools for typhoon identification and localization. Two-stage detectors such as R-CNN, Fast R-CNN, and Faster R-CNN have been successfully applied to typhoon detection tasks, offering high accuracy in both detection and localization [13]. These methods first generate region proposals and then classify and refine the detected objects.

Single-stage detectors, such as You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD), exhibit distinct advantages in computational efficiency while sustaining competitive levels of accuracy [14]. These frameworks are particularly valuable for operational applications where real-time processing is required. The RetinaNet architecture, with its focal loss function, has shown promising results in addressing the class imbalance problem common in typhoon detection tasks .

Recent advances in transformer-based architectures, such as DETR (Detection Transformer), represent a paradigm shift in object detection methodology [15]. These approaches treat object detection as a direct set prediction problem, potentially offering advantages in handling complex typhoon structures and multiple storm systems within a single image.

3.3. Semantic segmentation for typhoon structure analysis

Semantic segmentation techniques enable pixel-level classification of satellite imagery, providing detailed information about typhoon structure and components. U-Net, originally developed for biomedical image segmentation, has been successfully adapted for typhoon analysis due to its ability to preserve spatial details while capturing global context [16].

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The DeepLab series of networks, particularly DeepLabv3+ with its encoder-decoder architecture and atrous convolution, has demonstrated excellent performance in segmenting typhoon components such as the eye, eyewall, and rainbands. These detailed segmentations provide valuable input for subsequent intensity estimation and structure analysis.

4. Temporal modeling for typhoon tracking and prediction

4.1. Recurrent Neural Networks for sequential analysis

Typhoon tracking and intensity prediction inherently involve temporal sequences, making Recurrent Neural Networks (RNNs) and their variants particularly suitable for these tasks. Long Short-Term Memory (LSTM) networks address the vanishing gradient problem in traditional RNNs and can effectively model long-term dependencies in typhoon evolution .

Gated Recurrent Units (GRUs) offer a simplified alternative to LSTMs while maintaining comparable performance in many applications [17]. The reduced computational complexity of GRUs makes them attractive for operational forecasting systems where computational efficiency is crucial.

Bidirectional RNNs leverage both past and future information in the sequence, which can be valuable for typhoon analysis when the complete temporal sequence is available. This approach proves particularly valuable for typhoon reanalysis studies and for advancing the understanding of typhoon development processes.

4.2. Spatio-temporal fusion models

The combination of spatial and temporal modeling capabilities has led to the development of hybrid architectures that can simultaneously capture typhoon structure and evolution. ConvLSTM networks integrate convolutional operations within LSTM cells, enabling the model to learn spatio-temporal representations directly from satellite image sequences [18].

Three-dimensional CNNs provide another approach to spatio-temporal modeling by treating time as an additional dimension . These networks can capture temporal relationships while preserving spatial structure, making them well-suited for analyzing typhoon development patterns.

4.3. Attention mechanisms and transformer architectures

Attention mechanisms have brought about a paradigm shift in sequence modeling, as they enable models to selectively focus on the most relevant segments of the input sequence. In typhoon applications, attention can help models identify critical development phases or important structural features that influence future evolution.

Transformer architectures, based entirely on attention mechanisms, have shown remarkable success in various sequence modeling tasks. For typhoon prediction, transformers can model complex temporal dependencies and capture global relationships in the data without the limitations of recurrent architectures [19].

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5. Multi-modal data fusion strategies

5.1. Early and late fusion approaches

Multi-modal data fusion represents a critical aspect of modern typhoon monitoring systems. Early fusion approaches concatenate features from different sensors at the input level, allowing deep learning models to learn joint representations across modalities [20]. This approach is computationally efficient but may not optimally exploit the unique characteristics of each data source.

Late fusion strategies combine predictions from separate models trained on individual modalities. While this approach allows for specialized processing of each data type, it may miss important cross-modal interactions that could improve overall performance.

5.2. Cross-modal attention and adaptive fusion

Advanced fusion architectures employ cross-modal attention mechanisms that enable different modalities to influence each other's feature representations. These approaches can automatically learn the relative importance of different data sources for specific tasks and conditions.

Adaptive fusion networks adjust the contribution of different modalities based on data quality, availability, and relevance to the current prediction task [21]. This flexibility is particularly valuable in operational settings where sensor data may be incomplete or of varying quality.

6. Challenges and future directions

6.1. Current technical challenges

Despite significant progress, several challenges remain in applying deep learning to typhoon monitoring. Data quality issues, including cloud contamination, sensor calibration differences, and temporal coverage gaps, continue to affect model performance [22]. The relatively small number of extreme typhoon events in training datasets poses challenges for developing robust models that can handle rare but critical cases.

Model interpretability remains a significant concern for operational applications, where forecasters need to understand and trust model predictions. The "black box" nature of deep learning models can hinder acceptance and integration into existing forecasting workflows.

6.2. Emerging technologies and methodologies

Self-supervised learning approaches show promise for reducing dependence on labeled training data by learning useful representations from unlabeled satellite observations [23]. This is particularly valuable given the extensive archives of satellite data that lack detailed annotations.

Few-shot learning techniques could address the challenge of rare typhoon events by enabling models to learn from limited examples [21]. Transfer learning approaches that leverage knowledge from related meteorological phenomena or different geographical regions may also improve model robustness (Yosinski et al., 2014).

Physics-informed neural networks represent an exciting direction that incorporates physical constraints and meteorological knowledge directly into deep learning architectures [22]. These approaches could improve model reliability and extrapolation capabilities beyond training data distributions.

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7. Conclusion

The application of deep learning to typhoon monitoring using multi-modal remote sensing data represents a significant advancement in meteorological science and operational forecasting. These technologies have demonstrated superior performance in automated feature extraction, temporal modeling, and multi-source data integration compared to traditional methods.

Key achievements include the development of robust CNN architectures for typhoon detection and structure analysis, sophisticated temporal models for tracking and prediction, and effective fusion strategies for integrating diverse observation sources. These advances have improved the accuracy, objectivity, and computational efficiency of typhoon monitoring systems.

However, challenges remain in areas such as model interpretability, handling of rare events, and integration with existing operational frameworks. Future research should focus on developing more robust and interpretable models, incorporating physical constraints, and advancing real-time processing capabilities.

The continued evolution of satellite technology, computational resources, and deep learning methodologies promises further improvements in typhoon monitoring and prediction capabilities. As these technologies mature, they will play an increasingly important role in protecting lives and property from typhoon-related hazards, contributing to more resilient and prepared coastal communities worldwide.

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