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Enhanced Typhoon Center Localization Using Geostationary Satellite Imagery

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Key Points:

- A new and robust typhoon center localization algorithm using geostationary satellite imagery
- Smaller differences in typhoon center across all the intensities are found between the new locating algorithm and the best track results
- This methodology can be applied to advanced geostationary imager data for near real-time TC monitoring

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract An accurate center localization in near real-time is critical for tropical cyclone (TC) monitoring and forecasting. This study presents a robust algorithm for localizing typhoon centers using the Chinese geostationary (GEO) meteorological satellite. The results using the Advanced Geostationary Radiation Imager (AGRI) onboard Fengyun-4A (FY-4A) satellite data, achieving a mean absolute error (MAE) of 29.4 km across various typhoon intensities in the Western North Pacific, superior to other baseline methods. By harnessing the multi-spectral imagery from the FY-4A and incorporating an attention mechanism, it significantly boosts the deep learning convolutional neural network's ability to identify typhoon cloud features and their centers, even during their initial and weakest stages, which is laudable because these are the most difficult for center fixing even for human analysts. Remarkably, it requires just a single moment satellite imagery to locate the center of typhoon, enabling automated updates of the typhoon centers in near real-time applications.

Plain Language Summary Understanding and observing the exact location of the typhoon's center are crucial for monitoring and forecasting the storm path and intensity. Geostationary (GEO) satellites have become the primary means of continuously observing typhoon centers with Advanced Dvorak Technique (ADT). Nevertheless, locating the center from GEO observations more quickly and accurately is still desired for operational applications. For such purpose, a new algorithm that utilizes just a single moment images from a geostationary satellite to locate the center of typhoon rapidly and accurately has been developed. This method represents a significant improvement, capable of locating the center of typhoon with a mean absolute error of only 29.4 km, outperforming existing other baseline methods. Its sophisticated design allows it to discern intricate details of cloud features from multi-spectral satellite imagery, thus providing valuable insights particularly during the early stages of a typhoon's development.

1. Introduction

Typhoons, also referred to as tropical cyclones (TC), rank among the most devastating natural catastrophes on earth, incurring substantial economic losses annually (Rüttgers et al., 2019). With the ongoing changes in the global climate, the repercussions of TCs are anticipated to intensify in the coming years (Xu et al., 2024). Quickly and accurately locating the centers of TCs is crucial for disaster prevention and mitigation (He et al., 2021). For decades, the manual Dvorak Technique (DT) has been the cornerstone for typhoon center localization in satellite imagery, adopted by many official forecast centers across the globe (Velden & Olander, 2019). An advancement on this, the automated Dvorak method (ADT, Advanced Dvorak Technique), addresses some of the constraints of the manual approach (Velden & Olander, 2019). An improved version of the Automated Rotational Center Hurricane Eye Retrieval method (ARCHER-2) is a part of the ADT and is used to accurately locate the center of tropical cyclones, the median error of ARCHER-2 varies between 17 and 38 km (Wimmers & Velden, 2016). Additionally, the Automated Rotational Center Hurricane Eye Retrieval (ARCHER) method, which analyzes the cyclone's spiral structure to deduce its center, demonstrates heightened precision correlating with the TC's intensity. This method necessitates first guesses of the TC's geographical coordinates. The accuracy (RMSE) of the ARCHER is 17 km (9 km for category 1–5 hurricanes). In cases with estimated high vertical shear, the accuracy of the ARCHER is 31 km (21 km for category 2–5 hurricanes) (Velden & Wimmers, 2010).

In recent years, cutting-edge artificial intelligence (AI) techniques have revolutionized meteorological science, offering transformative approaches for forecasting and analysis, such as predicting extreme weather events and enhancing satellite retrieval (Bi et al., 2023; Min et al., 2020; Xia et al., 2024). Furthermore, it has been widely applied to locate the center of the typhoon. Yang et al. (2019) utilized manually annotated data sets derived from the tri-spectral infrared (IR) imagery of Japanese Himawari-8 GEO satellite to develop a typhoon identification network (ClaNet) and a typhoon center location neural network (LocNet). Wang et al. (2020) reconceptualized the challenge of typhoon center localization as a search problem, framing the quest for the typhoon's nucleus as a succession of Markov decision processes, and realized an impressive average deviation of 0.265°. In comparison, TCLNet (Typhoon Center Location Network) (Tan, 2021), an end-to-end neural network architected on a manually annotated typhoon data set, exhibited better precision over LocNet (Yang et al., 2019). Smith and Toumi (2021) leveraged the continuous IR channel imagery coupled with ConvLSTM (Convolutional Long Short-Term Memory) technology to locate the center of typhoon, achieving a median error of just 19.3 km and 95% error of 70.7 km. Long et al. (2022) compared six different deep learning models for locating the center of typhoon, with the YOLOv4 model achieving a confidence level of 99.84%, outperforming other methods tested in their study, with the lowest overall mean errors of 0.38° in longitude and 0.33° in latitude.

Considering the practical application scenarios, weather forecasters necessitate a robust and advanced algorithm for typhoon center localization in near real-time, integrated within software that not only demonstrates extensive applicability across diverse data sets but also ensures superior precision. Therefore, in this investigation, with the successive launches of the new generation geostationary satellites (e.g., China FY-4A satellite), our goal is to develop a new GEO-satellite-based algorithm or software to enable the rapid localization and near real-time tracking of typhoon centers, with higher accuracy and ease of use.

2. Data and Methods

2.1. Data

The FY-4A satellite, launched on 11 December 2016, is regularly managed by China's National Satellite Meteorological Center (NSMC) situated at a nadir of 104.7°E. It embodies a substantial advancement in geostationary quantitative remote sensing meteorological satellites in the globe (Guo et al., 2017). As one of primary payloads of the FY-4A GEO satellite, the Advanced Geosynchronous Radiation Imager (AGRI) provides observations with a remarkable temporal resolution of 5–15 min, covering the entire disk and China region, coupled with an impressive spatial resolution ranging from 0.5 to 4 km (Min et al., 2017). AGRI consists of six visible/near-infrared bands ranging from 0.47 to 2.25 μm, two mid-wave infrared bands (at 3.75 μm with high and low gains), and six long-wave infrared bands spanning from 6.5 to 13.5 μm. The multi-band radiance maps captured by FY-4A/AGRI will be employed here for the determination of typhoon center locations. Since the view zenith angles of TC samples studied here are significantly smaller than 60°, the relative parallax effect is negligible (error <1 km) in the typhoon center localization.

This study relies on the U.S. Joint Typhoon Warning Center (JTWC) as the primary source for vital typhoon path data, documenting the coordinates (longitude and latitude) of the center, maximum 1-min sustained wind speed, and minimum sea-level pressure (MSLP) of the typhoon at 6-hour intervals (UTC 00, 06, 12, and 18) (Song et al., 2010). It utilized JTWC data from 2017 to 2021 in the Northwest Pacific region to develop and test the typhoon center location algorithm software, which focuses specifically on samples ranging from tropical storms (TS) to Category−1–5 (Cat1-5) typhoons (1-minute sustained wind speed exceeds 34 knots). Tropical depressions (TDs) were excluded because their features are too indistinct (Wang et al., 2020).

2.2. Methods

In this study, an advanced deep convolutional neural network (CNN) model, called Improved-TCLNet, building on the foundational TCLNet (Tan, 2021), has been developed. TCLNet is a lightweight yet high-performing end-to-end model. The Improved-TCLNet processes multi-channel images of typhoons from AGRI, outputting a heatmap to pinpoint the typhoon center. The precise location of the typhoon center is identified by locating the peak value in this heatmap, as depicted in Figure 1. For more explanations and details, please refer to Figure S1 in Supporting Information S1, we offer more context to understand the distribution of the heatmap image and associated uncertainty. Being similar to TCLNet, Improved-TCLNet is structured around convolutional and residual blocks. Each convolutional block encompasses a convolutional layer, offering the flexibility to include or exclude batch normalization and Rectified Linear Unit (ReLU) as needed. The residual block is composed of three convolutional layers, each paired with batch normalization and ReLU activation functions. In cases where the input and output channel numbers of the convolutional layer vary, an extra convolutional layer is incorporated to

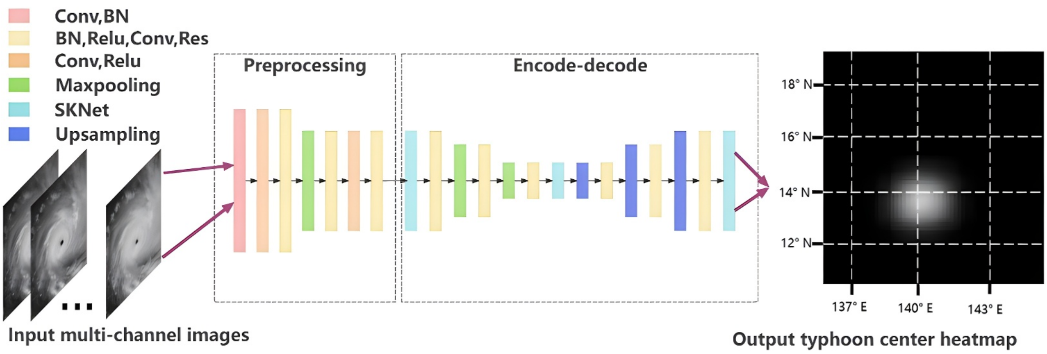

Figure 1. Schematic diagram of the framework of the Improved-TCLNet. Typhoon No. 26 in 2018.

align the number of channels. The model starts with a sequence of convolutional and residual blocks, tasked with extracting primary image features from the FY-4A imager data. Following this is an hourglass-shaped residual blocks structure, serving as an encoder-decoder. In the encoding stage, the feature map size is progressively reduced through downsampling, which helps preserve essential information while reducing computational load. Finally, the typhoon center heatmap is generated through a combination of upsampling operations and additional residual blocks in the decoding stage.

To enhance the extraction of critical features from the images, an attention mechanism called Selective Kernel Networks (SKNet, see Figure 1), was integrated within the new model. This mechanism judiciously selects convolutional kernels of different sizes and adaptively selecting the weights of these convolutional kernels by learning, thus enabling to model features at different scales (Li et al., 2019), improving the ability of feature extraction compared to using one single kernel, which perfectly complements the richer semantic hierarchy provided by the multi-channel satellite images as input. The careful selection of hyperparameters is also important for the training efficacy of the model. To optimize the model, focus was on iteratively fine-tuning hyperparameters such as activation functions, scheduler period, recovery period, learning rate, etc. Table S1 in Supporting Information S2 shows the range and the optimal values of these hyperparameters in the Improved-TCLNet.

Aiming the operational use scenarios in near real-time, based on the typhoon center coordinates from the JTWC, FY-4A/AGRI multi-channel Level-1B radiance data were processed, which included cropping and labeling. Data augmentation techniques were also applied to enrich the training and test data set during the data processing. The weather forecasters use their expertise to locate the center of a typhoon by interpreting real-time satellite imagery, which inherently introduces a notable degree of unpredictability. To make the center of the typhoon deviate from the center of the image, the images were cropped to dimensions of 350×350 pixels, and then sections with 224×224 pixels from these cropped images were randomly extracted. The typhoon center relative position within each subsection is meticulously documented as labels, as shown in Figure 2. The data were subsequently distributed into a training set and a test set, containing 90 (75,816 images) and 36 (38,808 images) typhoon samples in the Western North Pacific region respectively, adhering to a ratio of 7:3. To guarantee the robustness and generalizability of the experimental results, a consistent proportion of typhoons with diverse intensities was maintained across both sets, spanning the years 2017–2021 (see Table S2 in Supporting Information S2).

It is noteworthy that the mid-wave IR band at 3.75 μm shows limited stability due to solar irradiance interference, particularly around the terminator (Kimura et al., 2018). Consequently, this band is excluded in the localization model, and data from the other 12 bands of FY-4A/AGRI are used. Furthermore, in comparison to the previous Typhoon Center Location Data set (TCLD), our data set aforementioned is substantially larger, being 27 times the size and inclusive of tropical storms and typhoons across all intensity levels over 5 years. Employing JTWC data for annotations enhances the scientific credibility of our data set compared to those with manual annotations (Tan, 2021; Yang et al., 2019). This means our data set not only provides a greater volume of data but also a richer array of satellite detection channels within the typhoon images.

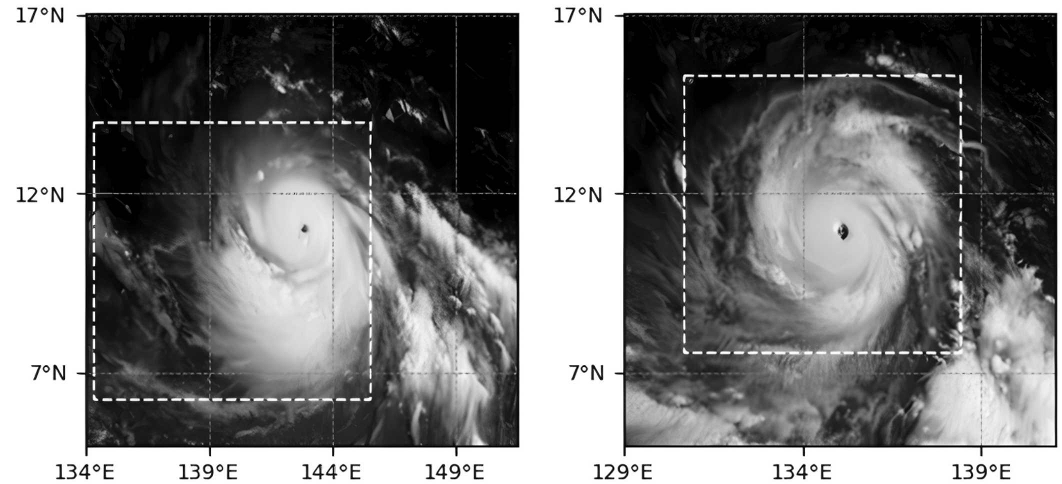

Figure 2. Randomly cropping typhoon image samples from FY-4A/AGRI observations at 00:00 UTC on 1 September 2018 (left panel) and 00:00 UTC on 12 September 2018 (right panel). The small box with white dashed line represents the cropped box with 224 × 224 pixels for typhoon samples.

3. Results and Discussions

Due to the absence of sunlight at night, satellite imagery data in the visible (VIS) and near-infrared (NIR) spectra are not available. Consequently, the data was categorized into two different sets: daytime data contain the VIS/NIR and IR wavelengths (IR + VIS), and nighttime data exclusively in the IR wavelength. The separate models were trained on these two data sets to enhance the accuracy of typhoon localization under all-day conditions. Daytime data provide more satellite image channels for the model to learn from, resulting in better model accuracy for weaker storms. During daytime, the model utilized VIS/NIR/IR data for its smaller errors, compared to the model for night, which only relied on IR data. Our final model of Improved-TCLNet integrates the insights from both training sets.

To validate the effectiveness of the Improved-TCLNet model, it was compared with the machine learning algorithm Random Forest (RF) (Breiman, 2001), non-machine learning algorithm of ARCHER (Velden & Wimmers, 2010), and the original TCLNet (Tan, 2021). The RF algorithm applied a grid search for parameter optimization and used a multi-output regressor wrapper for multidimensional regression outputs. For the ARCHER algorithm, initial latitude and longitude coordinates as a first guess are requisite inputs. It can accurately capture the spiral structure of typhoons, excelling with TC that displays well-formed eyewalls and convective spiral bands. Considering the average 24-hr forecast error for TC is approximately 70–80 km (Hsiao et al., 2020), a first guess that varied within ±0.8° from the best track data was supplied for ARCHER. The TCLNet model was trained on the updated data set using its established network structure and hyperparameters, utilizing only single-channel images input. We used the JTWC best track data set, which provides accurate typhoon center coordinates, as the truth for evaluating algorithm performance through the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics.

Table 1 presents the center localization errors of each method under different typhoon intensities on the test data set established in this study, which comprises 3,234 sets of multispectral GEO satellite data. Leave-One-Out Cross-Validation (LOO-CV) is the cross-validation technique we employed to assess the performance of Improved-TCLNet, the results are shown in Table 1. It demonstrates that Improved-TCLNet has good generalization capabilities. These are distributed across different typhoon categories as follows: 1,506 sets for TC and for Categories 1 through 5, there are 714, 360, 198, 282, and 174 sets respectively. In this table, the results show that the Improved-TCLNet achieves a MAE of 29.4 km and an RMSE of 48.6 km across all test data set instances, with the MAE for the highest intensity typhoon localization being only 11.7 km. The observed increase in localization errors for weak TC samples is due to the inherent complexity in learning their spiral structures, a challenge that ARCHER and TCLNet also encountered. Additionally, it is not surprising that a consistent trend of diminishing errors is apparent across all three methods as the intensity of the typhoon increases, and the significantly higher

Table 1
Comparison of MAE/RMSE (km) Values of Tropical Cyclones Center Localization Methods for Different Intensities

	TS	Cat1	Cat2	Cat3	Cat4	Cat5	All
RF	184.4/199.6	198.1/212.1	184.5/200.9	190.1/209.2	192.3/203.8	175.8/190.6	188.1/203.1
ARCHER	182.4/212.6	130.9/182.6	123.6/177.3	81.4/137.3	24.3/57.8	18.8/58.0	135.7/183.1
TCLNet	99.1/126.8	58.1/76.8	47.5/60.9	41.8/55.9	33.0/38.3	22.9/25.9	69.7/96.6
Improved_TCLNet without SKNet	110.7/145.6	79.3/99.6	60.4/77.4	55.5/62.3	42.7/50.0	30.1/40.2	84.5/103.1
IR Improved-TCLNet	45.7/72.0	22.7/30.8	19.9/26.1	14.8/18.5	10.3/12.1	9.1/10.8	30.8/52.3
IR + VIS Improved-TCLNet	37.5/55.9	22.1/29.9	20.6/25.7	16.6/20.9	15.4/18.5	14.5/16.9	27.5/42.0
Improved-TCLNet	41.6/65.8	22.5/31.2	20.2/25.6	16.3/20.5	13.0/15.7	11.7/14.2	29.4/48.6
LOO-CV	13.3/48.4	10.3/23.0	8.4/8.9	8.2/8.8	8.2/8.7	8.5/8.9	11.2/30.7

number of weaker typhoons compared to stronger typhoons leads to larger MAE and RMSE in total (see Table S3 in Supporting Information S2), especially for ARCHER.

Besides, the RF model exhibits significant errors due to its lower complexity, making it less suitable for the intricate task of cloud structure and feature extraction, as well as precise typhoon center localization. Notably, Improved-TCLNet demonstrates superior accuracy compared to other methods, with a reduction of 84.4% and 76.1% in MAE and RMSE compared to RF, 78.3% and 73.5% compared to ARCHER, and 57.8% and 49.7% compared to the original TCLNet, respectively. These results affirm the effectiveness of the Improved-TCLNet method. Moreover, in comparison to the ARCHER algorithm, the MAEs from TS to Cat5 storms have been reduced by 77.2%, 82.8%, 83.7%, 80.0%, 46.5%, and 37.8%, respectively, with the Improved-TCLNet. In contrast to the original TCLNet, the reductions are 58.0%, 61.3%, 57.5%, 61.0%, 60.6%, and 48.9%, respectively. Particularly, the Improved-TCLNet demonstrates significant accuracy enhancements for low-intensity typhoons, which are typically challenging to pinpoint with precision.

Figures 3a–3c show TC with lower central wind speeds, from TS to Cat2, with central 1-min wind speeds between 34 and 83 knots. In these scenarios, where the typhoon embryo and an eyewall may be absent or indistinct, the Improved-TCLNet and TCLNet methods demonstrate a notable advantage in accuracy. Conversely, Figures 3d–3f illustrate TC with higher wind speeds, from Cat3 to Cat5, with central wind speeds exceeding 83 knots. Here, the presence of a distinct typhoon eye enhances ARCHER's precision. Kim et al. (2019) noted that the RF method provided an improved performance for detecting TC formation compared with other approaches. Nonetheless, the RF method's capacity to locate TS center via satellite imagery is less than ideal. While the TCLNet algorithm generally yields small center localization errors, it achieves superior proximity to the JTWC best track data, benefitting from its enhanced learning across various satellite data channels and network structure optimization.

Compared to using IR data alone, incorporating both IR and VIS data as input improves performance at TS-Cat2 intensities. However, the accuracy of model is significantly related to the size of the data set (see Figure S3 in Supporting Information S1). The accuracy decreases at Cat3-Cat5 intensities due to the insufficient number of high-level typhoon daytime data samples (see Table S3 in Supporting Information S2). In real scenarios, it is not always possible to accurately determine the exact typhoon intensity in advance. Therefore, we divided the data into daytime and nighttime data sets for training, aiming to achieve higher overall accuracy. Improved-TCLNet, using data from 2017 to 2020 as the training set and data from 2021 as the testing set, achieves similar accuracy results (see Table S4 in Supporting Information S2 and Figure S2 in Supporting Information S1).

Contrary to Smith and Toumi (2021), which necessitates the use of multiple sequential satellite images for training and prediction based on ConvLSTM, the Improved-TCLNet attains superior localization precision utilizing just one single time satellite image source. Figure 4 demonstrates the performance of ARCHER, TCLNet, and Improved-TCLNet methods by examining four typhoon cases, HATO, LEKIMA, HAISHEN and MARIA, both of which made landfall in mainland China. Due to the comparatively large errors of the RF model, its results are omitted from the figure. The findings indicate that all methods experience a notable increase in typhoon center localization errors when TS are initially forming over the ocean or after landfall,

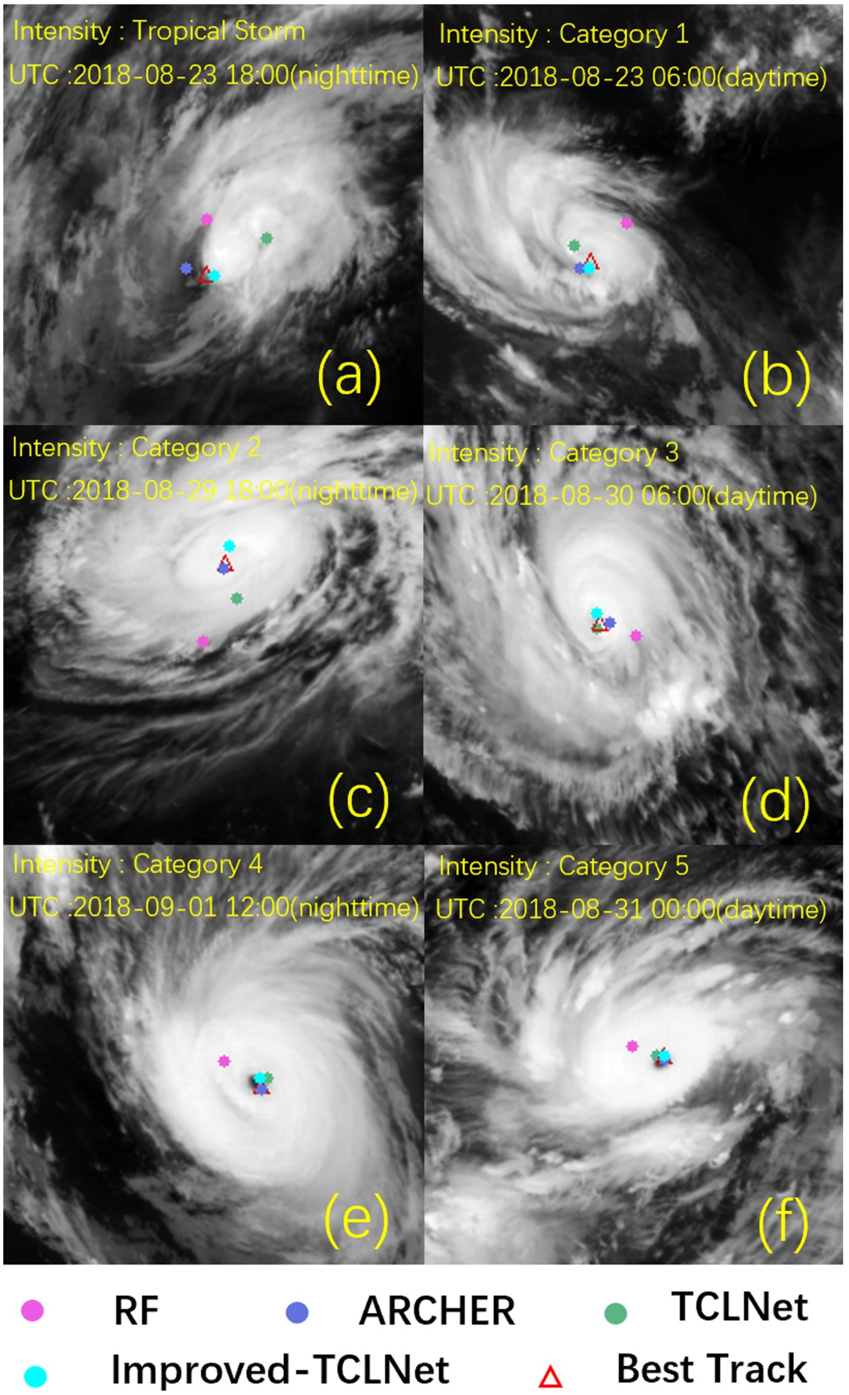

Figure 3. IR brightness temperature images of Super Typhoon JEBI at various intensities in 2018. The center localizations derived from RF, ARCHER, TCLNet, and Improved-TCLNet methods are distinguished by different markers. Red triangle markers represent the JTWC best track positions for the typhoon center.

attributed to complex and volatile meteorological conditions. Of these methods, ARCHER algorithm shows the most significant error variability, while Improved-TCLNet method still maintains greater overall stability. During the life cycles of the two typhoons examined, the Improved-TCLNet method consistently kept center localization errors around 30 km.

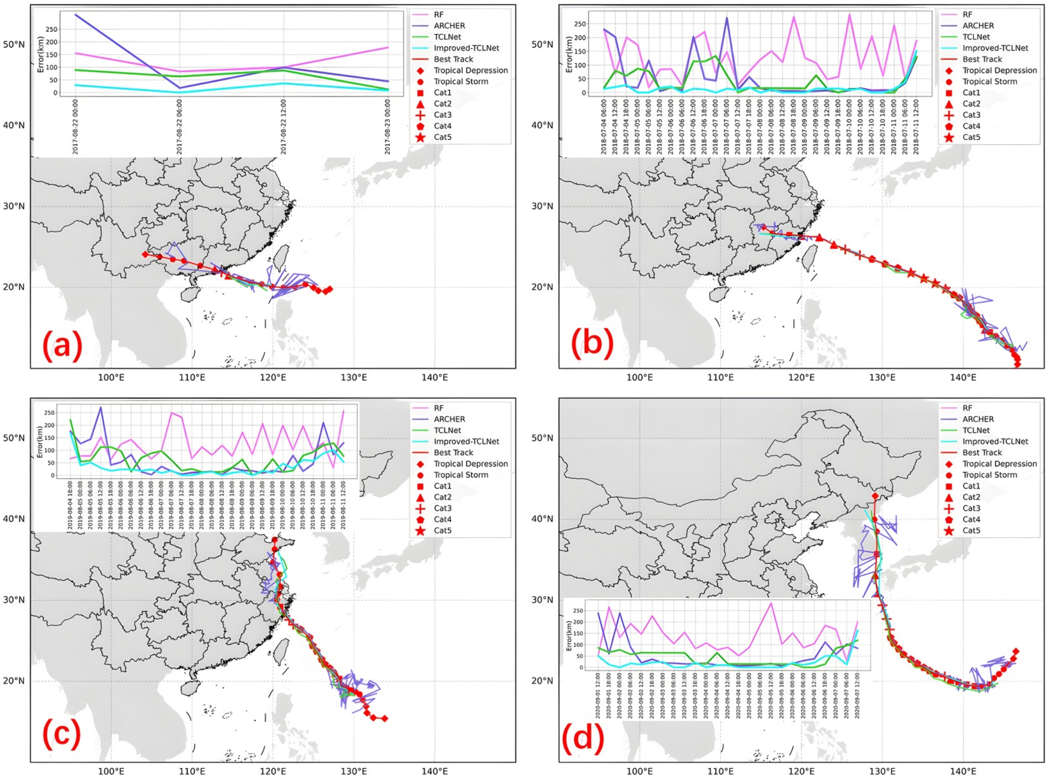

Figure 4. Trajectory maps obtained from the center localization of Typhoon HATO in 2017 (a), Typhoon MARIA in 2018 (b), Typhoon LEKIMA in 2019 (c), and Typhoon HAISHEN in 2020 (d) by various methods. The JTWC best track path is concurrently shown, with updates every 6 hr, while the methods present updates every 15 min. The embedded subfigures depict the errors of each method relative to the best track at UTC 00, 06, 12, and 18.

4. Conclusions

In this study, we proposed an advanced Improved-TCLNet method designed for real-time typhoon center localization. The incorporation of the SKNet improved our model's ability to extract critical features from satellite images and aligned well with the rich semantic information in multi-channel inputs. It has been tested on a data set comprising 9,552 sets satellite images of typhoons in the Western North Pacific, taken from FY-4A/AGRI with a 4 km spatial resolution spanning 2017 to 2021, and has achieved a MAE of 29.4 km and a RMSE of 48.6 km for all the typhoon cases across all the intensities. These results mark a significant advancement with an accuracy improvement of over 30% compared to other baseline methods, including the original TCLNet and the ARCHER algorithms. Note that, the challenge of accurately determining the centers of low-intensity typhoons, often characterized by incomplete eyewalls and asymmetrical structures, is notably addressed by the Improved-TCLNet. It augments the deep learning network's capacity to discern typhoon cloud features through the integration of attention mechanisms, thereby enabling precise center localization at their initial stages. Furthermore, the adoption of multi-channel satellite imagery enriches the semantic hierarchy, thereby enhancing the model's ability to interpret the content within images more thoroughly. The Improved-TCLNet leverages this multi-channel input, thereby significantly improving the accuracy of typhoon center localization.

This new method can be used for monitoring TC in near real-time, thus has the potential to operationalize. It should be noted that training data set is important to building such a localization model, it is ideal to apply such model to GEO satellite imager data with long time consistency, for example, to the AHI data from Himawari-8 to Himawari-9. It is expected to achieve higher accuracy on data sets with higher spatial resolution of space-borne imager. With the new instrument, the model training needs to be updated with more observations available, after the model is trained with sufficient training data, it can be applied for operational TC monitoring and forecasting.

Data Availability Statement

Fengyun-4A satellite data (Min et al., 2017) used in this study are freely downloaded from the official website of National Satellite Meteorological Center, CMA at http://satellite.nsmc.org.cn/PortalSite/Data/DataView.aspx?currentculture=en-US. Open-source code of ARCHER (Wimmers & Velden, 2016) is available from https://github.com/ajwimmers/archer/tree/main. Resized satellite imageries and codes for typhoon center localization test in this investigation are available from https://doi.org/10.6084/m9.figshare.25256305.v4 (Zhou, 2024).

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References

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, *619*(7970), 533–538. https://doi.org/10.1038/s41586-023-06185-3

Breiman, L. (2001). Random forest. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/a:1010933404324

Guo, Q., Lu, F., Wei, C., Zhang, Z., & Yang, J. (2017). Introducing the new generation of Chinese geostationary weather satellites, Fengyun-4. *Bulletin of the American Meteorological Society*, *98*(8), 1637–1658. https://doi.org/10.1175/bams-d-16-0065.1

He, B., Yu, Z., Tan, Y., Shen, Y., & Chen, Y. (2021). Rainfall forecast errors in different landfall stages of Super Typhoon Lekima (2019). *Frontiers of Earth Science*, *16*(1), 34–51. https://doi.org/10.1007/s11707-021-0894-9

Hsiao, L.-F., Chen, D.-S., Hong, J.-S., Yeh, T.-C., & Fong, C.-T. (2020). Improvement of the numerical tropical cyclone prediction system at the central weather Bureau of Taiwan: TWRF (typhoon WRF). *Atmosphere*, *11*(6), 657. https://doi.org/10.3390/atmos11060657

Kim, M., Park, M.-S., Im, J., Park, S., & Lee, M.-I. (2019). Machine learning approaches for detecting tropical cyclone formation using satellite data. *Remote Sensing*, *11*(10), 1195. https://doi.org/10.3390/rs11101195

Kimura, T., Xiong, X., Guo, Q., Min, M., Gao, L., Zhang, Y., et al. (2018). On-orbit calibration analysis of FY-4A AGRI solar bands. In *Paper presented at the earth observing missions and sensors: Development, implementation, and characterization V*.

Li, X., Wang, W., Hu, X., & Yang, J. (2019). Selective kernel networks. In *Paper presented at the Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*.

Long, T., Fu, J., Tong, B., Chan, P., & He, Y. (2022). Identification of tropical cyclone centre based on satellite images via deep learning techniques. *International Journal of Climatology*, *42*(16), 10373–10386. https://doi.org/10.1002/joc.7909

Min, M., Li, J., Wang, F., Liu, Z., & Menzel, W. P. (2020). Retrieval of cloud top properties from advanced geostationary satellite imager measurements based on machine learning algorithms. *Remote Sensing of Environment*, *239*, 111616. https://doi.org/10.1016/j.rse.2019.111616

Min, M., Wu, C., Li, C., Liu, H., Xu, N., Wu, X., et al. (2017). Developing the science product algorithm testbed for Chinese next-generation geostationary meteorological satellites: Fengyun-4 series. *Journal of Meteorological Research*, *31*(4), 708–719. https://doi.org/10.1007/s13351-017-6161-z

Rüttgers, M., Lee, S., Jeon, S., & You, D. (2019). Prediction of a typhoon track using a generative adversarial network and satellite images. *Scientific Reports*, *9*(1), 6057. https://doi.org/10.1038/s41598-019-42339-y

Smith, M., & Toumi, R. (2021). Using video recognition to identify tropical cyclone positions. *Geophysical Research Letters*, *48*(7). https://doi.org/10.1029/2020gl091912

Song, J. J., Wang, Y., & Wu, L. (2010). Trend discrepancies among three best track data sets of western North Pacific tropical cyclones. *Journal of Geophysical Research*, *115*(D12). https://doi.org/10.1029/2009jd013058

Tan, C. (2021). TCLNet: Learning to locate typhoon center using deep neural network. In *Paper presented at the 2021 IEEE international geoscience and remote sensing symposium IGARSS*.

Velden, C. S., & Olander, T. L. (2019). The Advanced Dvorak Technique (ADT) for estimating tropical cyclone intensity: Update and new capabilities. *Weather and Forecasting*, *34*(4), 905–922. https://doi.org/10.1175/waf-d-19-0007.1

Velden, C. S., & Wimmers, A. J. (2010). Objectively determining the rotational center of tropical cyclones in passive microwave satellite imagery. *Journal of Applied Meteorology and Climatology*, *49*(9), 2013–2034. https://doi.org/10.1175/2010jamc2490.1

Wang, P., Wang, P., Wang, C., Yuan, Y., & Wang, D. (2020). A center location algorithm for tropical cyclone in satellite infrared images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 2161–2172. https://doi.org/10.1109/jstars.2020.2995158

Wimmers, A. J., & Velden, C. S. (2016). Advancements in objective multisatellite tropical cyclone center fixing. *Journal of Applied Meteorology and Climatology*, *55*(1), 197–212. https://doi.org/10.1175/jamc-d-15-0098.1

Xia, P., Zhang, L., Min, M., Li, J., Wang, Y., Yu, Y., & Jia, S. (2024). Accurate nowcasting of cloud cover at solar photovoltaic plants using geostationary satellite images. *Nature Communications*, *15*(1), 510. https://doi.org/10.1038/s41467-023-44666-1

Xu, J., Zhao, P., Chan, J. C., Shi, M., Yang, C., Zhao, S., et al. (2024). Increasing tropical cyclone intensity in the western North Pacific partly driven by warming Tibetan Plateau. *Nature Communications*, *15*(1), 310. https://doi.org/10.1038/s41467-023-44403-8

Yang, X., Zhan, Z., & Shen, J. (2019). A deep learning based method for typhoon recognition and typhoon center location. In *Paper presented at the IGARSS 2019–2019 IEEE international geoscience and remote sensing symposium*.

Zhou, Z. (2024). Improved-TCLNet. *Figshare. Online resource*. https://doi.org/10.6084/m9.figshare.25256305.v4