Estimation of Tropical Cyclone Intensity Using Infrared Data from a Geostationary Satellite

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Abstract

Accurate estimation of tropical cyclone (TC) intensity is of great significance for serious natural disasters. A new method is presented to estimate intensity of TC using satellite infrared data. Firstly, TC region is calculated according to the location of TC center. Secondly, 2D-PCA algorithm is used to extract feature of bright temperature image, and historical data of TC intensity is matched with the k-nearest neighbor algorithm. Thirdly, the matching results are analyzed and the intensity information of TC is estimated. In addition, a TC intensity database, which contains historical data during 2006–2010, is developed for estimation of TC intensity. Experiments show that the proposed method is efficient for real-time estimation of TC intensity, average error of estimation is lower than 15 hPa.

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1. Introduction

Tropical cyclone (TC), particularly intense ones, may cause serious natural disasters. An assessment of changes in TC intensity has important socioeconomic implications. Meteorological satellite, which has a wide coverage, collects monitoring data, such as meteorological, hydrological and oceanographic (Machado et al. 1998).

In the past, a number of techniques for estimation of TC intensity were proposed by scholars and researchers. Zhang et al. (2014) analyzed intensity of Atlantic storms during 2008–2012 utilizing the forecasting model. Zhuge et al. (2015) developed a method for estimation of TC current intensity using infrared and water vapor imagery, the imagery came from a geostationary satellite. Villarini and Vecchi (2013) employed global climate models to examine projections in North Atlantic PDI. PDI was integrated as a metric based on a statistical model described in the past. Sobel et al. (2016) reviewed projections of future TC activity and discussed recent historical trends in PI and TC activity. Emanuel and Zhang (2016) compared control and perturbation experiments, and used the CHIPS model to address the relative importance in a perfect model framework. Dataset from 1998 to 2012 were used to quantitatively compare the precipitation, and a new metrics was developed to quantitatively compare the precipitation (Alvey et al. 2015).

Xu et al. (2017) examined characteristics of TC total lightning in all TCs, and addressed five fundamental questions. In order to explore the sensitivity of TCs and identify effects of climate change, three HiFLOR experiments were performed (Bhatia et al. 2018). TC intensity prediction was investigated using a statistical-dynamical model, the model is named SHIPS (Yamaguchi et al. 2018). Bhatia et al. (2017) updated BN15 and developed PRIME to improve TC intensity forecasts for the east Pacific basin. Na et al. (2018) investigated relation between various directions of VWS and intensity change of TC. Lu and Yu (2013) proposed a model using statistical relationship based on satellite images, the relationships between TC intensity and inner-core convection, and so on. The model have six significant factors, including number of convective cores, $V_{max}$ six hours previous ($V_{6h}$), latitude of TC center and longitude of TC, $DIS_{min}$ (minimum distance between convective cores and TC center) and $TBB_{max}$ (difference between the maximum and minimum blackbody temperature (TBB) value of convective cores). The TC intensity estimation model was set up by the stepwise regression method (SRM). The number of convective cores was determined by TBB slope and threshold value using IR images. Fetanat et al. (2013) proposed a new method using a k-nearest-neighbor algorithm based on brightness temperature profiles, and tried to estimate TC intensity using historical satellite imagery. The method showed estimation errors of 8.4 hPa and 10.9 kt. Chen et al. (2019) proposed a deep-learning model based on convolutional neural network (CNN) for estimating TCs, and the method showed a root-mean-square intensity difference of 8.39 kt. Compared with the previous studies, the present method has a high real-time performance. Processing speed of the proposed method is faster than that of the previous methods. In this work, we performed intensity estimation by the SRM and ETCI methods, the processing speed for these two methods were 8.7s and 7.6s, respectively.

To summarize, a number of methods proposed by researchers usually use model to estimate TC intensity but the percentage of correct estimation is low. To address this issue, a novel algorithm was developed for estimation TC intensity (ETCI) based on two-dimensional principal component analysis (2D-PCA) algorithm (Yang et al. 2004).

In order to calculate intensity of TC, a TC intensity database firstly conducted according to historical data provided by China meteorological administration (CMA) during 2006–2010. TC intensity database was first proposed by us and will be employed as the basis of TC estimation. First, TC region is calculated according to the location of the TC center. Second, 2D-PCA algorithm is used to extract feature of bright temperature image, and historical data of TC intensity are matched with the k-nearest neighbor algorithm. Third, the matching results are analyzed and intensity information of TC is estimated.

2. Data and method

2.1 Satellite data

Brightness temperatures information in infrared channel of Feng Yun-2F (FY-2F) satellite is used in experiment in this work. FY-2F has flexible capability of scanning in specific areas, and specified the observation for severe weather such as rainstorm, hail and TC. FY-2F plays an important role in meteorological disaster monitoring and early warning, disaster prevention and reduction in China. As shown in Table 1, FY-2F satellite imager radiometric channels are composed of infrared (IR) 1, IR 2, water vapor (WV) channel, IR 4 and visible (VIS) channel. Channel WV and Channel IR3 are same channel. WV channel is a special type of infrared channel from which atmospheric moisture content can be observed. Channel VIS has a higher spatial resolution than channel IR. Data from VIS channel are utilized for weather observations in the daytime. The wavelength and spatial resolution of these channels are different. Temporal resolution of FY-2F satel-
The presented methods and five-year data collected by us are utilized to construct the training set data for TC intensity estimation. Next, intensity of TC is estimated using 2D-PCA. TC image similarity is measured by Euclidean distance between samples, in TC database that are most similar to testing sample. The 2D-PCA algorithm constructs the covariance matrix from IR images directly, mapping IR images to projection space and calculating feature representation. The procedure of ETCI algorithm is given below:

Input:  
TC image I, TC database D  
Output:  
Estimated TC intensity T  

Step 1: TC image preprocessing.  
Step 2: Average image \( \bar{I} \) of all the training sample is compute,  
\[
\bar{I} = \frac{1}{M} \sum_{i=1}^{K} I_i^j
\]  
where \( N \) denotes the number of TC intensity categories, \( K \) represents number of samples for each strength in TC database, and \( M \) is the number of all samples, namely \( M = KN \), which is the \( J_{120} \) sample of class \( I \). Next, covariance matrix of these samples are calculated by us:

\[
COV = \frac{1}{M} \sum_{i=1}^{K} (I_i^j - \bar{I}) (I_i^j - \bar{I})^T
\]

Then, the eigenvalues of covariance matrix \( COV \) are calculated by us, and the corresponding normal orthogonal eigenvectors \( X_1, \ldots, X_p \) of the largest \( p \) eigenvalues \( u_1, \ldots, u_p \) are selected as the basis of projection space. \( u_1, \ldots, u_p \) are the largest \( p \) eigenvalues of covariance matrix \( COV \).

All the sample data are projected by the projection vector

\[
Y_i^j = [I_i^jX_1, \ldots, I_i^jX_p] = [Y_i^j(1), \ldots, Y_i^j(p)] \in \mathbb{R}^{m \times p}
\]

Where, \( X_1, \ldots, X_p \) is the basis of the projection space, \( I_i^j \) is the \( j \)th sample of class \( i \) and \( Y_i^j \) is the projection coordinates of \( I_i^j \) in the projection space, \( m \) is dimension in \( \mathbb{R}^{m \times p} \).

The presented methods and five-year data collected by us are utilized to construct the training set data for TC intensity estimation. Next, intensity of TC is estimated using 2D-PCA. TC image is projected into space \( X_1, \ldots, X_p \), and its characteristic representation in the projected space can be represented as

\[
Y = [Y(1), \ldots, Y(p)] = [WX_1, \ldots, WX_p]
\]

where \( W \) is TC sample which need to be predicted, and \( Y \) is the projection representation of \( W \) in space \( X_1, \ldots, X_p \). Next, k-nearest neighbor algorithm is used to search k-training samples in TC database that are most similar to testing sample \( W \). The similarity is measured by Euclidean distance between samples, namely, the smaller the Euclidean distance, the more similar the two samples. Euclidean distance can be represented as follows

\[
p(Y_i^j, Y) = \sum_{n=1}^{p} \| Y_i^j(n) - Y(n) \|^2
\]

where \( p(Y_i^j, Y) \) represents Euclidean distance between two samples. Euclidean distance between testing samples and all training samples is calculated and k-training samples with the smallest distance are found by us, and mean intensity of k samples is calculated as TC intensity of testing samples.

Step 7: The averaged value of TC intensity of k-samples will be regarded as the intensity of TC.

3. Results and discussion

3.1 Case study

TC data from 2006 to 2010 are chosen as training set, and data from 2011 to 2012 will be utilized to test TC intensity. Intensity results in the best path of TC provided by CMA are compared with the results of the proposed algorithm. Case studies selected in this section are TC Halong, Matmo and Neoguri in 2014. TCs mostly occur in July, August and September in the Northwest Pacific. Therefore, these three TCs which happened in July 2014 have been chosen for analysis in this work.

Firstly, histogram equalization and median filtering were utilized to reduce the influence of disturbance. Histogram equalization is an image enhancement technique which can improve the contrast details and the dynamic range of gray level of image. Median filtering method was selected to eliminate image noises. Figure 1 is sample images and results of TC Halong after preprocessing. Three sample images are 1200 UTC on 31 July 2014, 0000 UTC on 3 August 2014 and 1200 UTC on 8 August 2014, respectively. These images of TC Halong are at the stages of formation, maturity and dissipation. Figure 2 shows the intensity change of TC Halong in lifecycle. As shown in Fig. 1, images in the first row are sample images, the second row are result of sample image after histogram equalization, and the third row are result after median filtering. Then, the 2D-PCA algorithm was used to extract the features of bright temperature image, and the k-nearest neighbor algorithm was utilized to match historical data of TC intensity.

| Table 1. Satellite imager radiometric channels of FY-2F. |
|-----------------|-----------------|-----------------|-----------------|
| Channel | Wavelength (µm) | Spatial Resolution (km) | Used |
| IR1     | 10.3–11.3       | 5                | √              |
| IR2     | 11.5–12.5       | 5                | √              |
| WV      | 6.3–7.6         | 5                |                 |
| IR4     | 3.5–4.0         | 5                |                 |
| VIS     | 0.55–0.90       | 1 & 5            |                 |

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In present study, TC intensity estimation algorithm is verified and compared with the intensity estimation results from the optimal path database given by CMA. The smaller the error, the more accurate the algorithm is.

Results for intensity estimation obtained by the proposed algorithm are compared with the best results for intensity estimation given by CMA, and compared with popularized method SRM (Lu and Yu 2013) which is a mainstream method at present (See Figs. 2, 3, and 4).

As shown in Figs. 2, 3, and 4, intensity estimation of the proposed algorithm is the nearest to the optimal intensity given by the CMA. Among them, the average error of Halong is 9.13 hPa, the average error of Matmo is 11.61 hPa, and the average error of Neoguri is 10.42 hPa. Errors of SRM method for intensity estimation of these three TCs are 9.67 hPa, 12.54 hPa and 11.32 hPa, respectively. Therefore, compared with SRM method, error of proposed method is smaller.

### 3.2 Comparison of ETCI with other methods

The proposed algorithm is utilized to calculate the intensity of all TCs from 2011 to 2012, and compared with SRM and the optimal intensity dataset given by CMA.

Table 2 shows the intensity estimation error of TCs during 2011 to 2012. It can be seen that the proposed algorithm estimates TC intensity accurately and error in the proposed method is relatively smaller than that in SRM. Average error of the present method and SRM are 13.79 hPa and 13.96 hPa, respectively. This illustrates the proposed method estimate TC intensity more accurately than SRM method.

### 4. Conclusion

A new method called ETCI is presented for estimating TC intensity. A TC intensity database that first proposed by us was conducted according to historical data during 2006–2010. 2D-PCA based algorithm was proposed to estimate TC intensity using the database created by us. Feature of bright temperature image was extracted using 2D-PCA algorithm. Furthermore, historical data of TC intensity were matched with the k-nearest neighbor algorithm. The effectiveness of the proposed algorithm was verified by experiments on three TCs (Halong, Matmo and Neoguri), and the
best path provided by CMA. Various experiments show that average errors of the proposed ETCI method are lower than 15 hPa.

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