S131 TROPICAL CYCLONE INTENSITY ESTIMATION FROM SATELLITE IMAGES

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1. INTRODUCTION

Accurate intensity estimation of tropical cyclones (TC) is an important topic of research due to their economic impact and public safety concerns. An accurate measure of the current wind strength is necessary to accurately predict TC intensity. Wind measurement is obtained by aircraft flying through the cyclones, however routine flights occur only in the North Atlantic Ocean. Meteorologists also use satellite images to infer the wind strength. The Dvorak technique (DT) is the state-of-the-art method that has been used over three decades for estimating the intensity of a tropical cyclone (Velden et al. 2006) using satellite images. The DT subjectively estimates TCs' intensity based on visible and infrared satellite images (Dvorak 1984). Improvement of the original DT evolved into the objective Dvorak technique (ODT), which used computer based analysis to estimate intensity (Velden and Olander 1998). To overcome the limitations of the ODT, such as manual selection of the storm center or the inability to operate on weak storms, the advanced objective Dvorak technique (AODT) was developed. The most recent version of ODT is the advanced Dvorak technique (ADT) (Olander and Velden 2007). Unlike the ODT and AODT, whose focuses were to mimic the subjective technique, the ADT concentrates on extending the method beyond the original application and constraints.

Our new algorithm for estimating intensity used features of satellite images as predictors of the TCs' intensity. We hypothesized that we could discover unknown regularities and abnormalities in the large group of past observations and use them to help human experts interpret changes in TCs' intensity. This research was inspired by the availability of satellite imagery for tropical cyclones. Our goal was to provide a data mining tool which developed a new automated technique for TC estimation using hurricane satellite (HURSAT) data.

The remainder of the paper is organized as follows: section 2 provides the information about the data used for this study. Section 3 describes the methods used in image analysis. Section 4 discusses the validation process and the results, and section 5 provides a summary and a discussion of future work.

2. DATA

This Hurricane satellite data (HURSAT–B1, version 05) described in Knapp and Kossin (2007) provides infrared imagery for global tropical cyclones from 1978-2009. HURSAT–B1 data files are in a network common data form (NetCDF) format, in which each file is a snapshot of the storm from one or more of the international geostationary weather satellites. The infrared satellite images with the best view (that is, the smallest view zenith angle) were considered for this study.

In this study, we focus on a subset of North Atlantic storms for which there were contemporaneous low-level aircraft-measured intensities. Following Kossin et al. (2007), the training data was restricted to include fixes that are over water and are south of 45˚N. We considered the best track intensity estimates to be those with aircraft reconnaissance within 12 hours. This subset comprised 2,016 measurements in 165 storms from 1988 – 2006.

From HURSAT we derived the mean and standard deviation (SD) of brightness temperature (BT in Kelvin) for 70 azimuthal rings in 10 km bins from the storm center (5km, 15km, 25km... 695km). These are used as predictors for measuring the similarity (closeness) in Euclidean space for different storms.

3. METHODOLOGY

Our new technique used the *age* (or duration) of the cyclone and imagery from the *current* time along with imagery from 6, 12 and 24 hours before the current time to estimate the intensity. The *age* of the cyclone refers to the approximate time elapsed between *present* (time of intensity estimation) and the starting time of the storm (Fetanat et al., 2012). The *current* and the preceding 6, 12 and 24 hour images expressed by BT (mean and SD) of the selected rings around the center of the storm.

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The new technique for estimating intensity is illustrated in Figure 1. First, the data in the training set were organized according to selected features (*age*, and *current* and the preceding 6, 12, 24 hours' images). Second, for each query entry the same features were extracted. The third and the forth steps were used for sorting similar entries from training set first based on *age*, followed by the *current* and prior BT of the images for a given query. The sorting was performed in this order since the units of the features, *age* (hour) and BT (Kelvin), are different. Similarity was defined in terms of Euclidian distance between the query entry and all of the training entries.

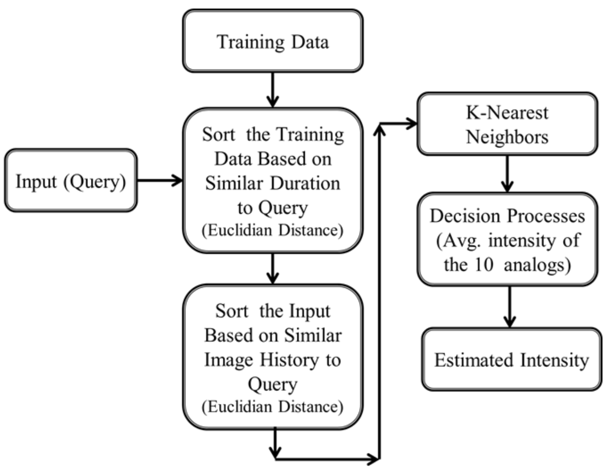

Figure 1: Block diagram of the new technique for image analysis

The third step consisted of searching the training data based on only similar durations. All entries in the training data were sorted in ascending order based on the computed Euclidian distance between the duration (in hours) of the query entry and entries from the training set. The entry from the training data with the shortest distance (most similar duration) was set as the first entry of the sorted training entries.

In the fourth step, the sorted entries (i.e., of step three) were sorted again based on the Euclidian distance between the current and previous BT of the images of the query entry and the corresponding features of the training entries. In this step, BTs mean and SD of the selected image rings were used for comparison. A sequential forward selection (SFS) algorithm (Koutroumbas, 1999) was used to find the optimum number of the rings for similarity comparison. In this algorithm, each ring was sequentially added to an empty candidate set until the addition of further rings did not decrease the criterion. The criteria used were the mean absolute error (MAE) and root mean square error (RMSE). Instead of focusing on whether the estimated values were an exact match with the real-values, the accuracy was measured in terms of the difference between the predicted values and the actual values. The loss functions measure the error among actual values and the estimated values. The most common loss functions are MAE and RMSE (Han and Kamber 2006). Finally, 14 rings out of a possible 70 rings around the center of the storm were selected using the SFS algorithm for comparison as described in section (4.1).

Fifth, we applied the K-nearest neighbor algorithm to classify K entries with the shortest Euclidian distance. Each entry was described by 112 attributes (or features). Each training entry represented a point in a 112-dimensional space. When presented with a query with an unknown intensity, a K-nearest-neighbor classifier searched the 112-dimensional space for the K training entries that were closest to the unknown entry. “Closeness” was defined in terms of the Euclidean distance. These K entries were the K “nearest neighbors” of the unknown query entry.

Sixth, the estimated intensity of the query entry was the average intensity value of the 10 nearest neighbors. The algorithm's performance was affected by the choice of K. If K was small, then the algorithm could be affected by noisy points. If K was too large, then the nearest neighbors could have belonged to different classes. By changing the value of K from 1 to 200 for several validation processes, the optimum value appeared to be 10, which had a minimum averaged error in terms of MAE and RMSE.

An example was provided to clarify our new technique. Consider the query entry to be Hurricane Katrina at 1200 UTC 27 August 2005 (Figure 2). The goal was to estimate the intensity corresponding to the given query entry at that given date and time. The nearest neighbor to Hurricane Katrina at that time using the method described above was from the training set for Hurricane Gustav at 0000 UTC 28 August 1990 (Figure 3); Gustav’s intensity was 95 kt. This happened to be only 5 kt from the estimated intensity of Katrina of

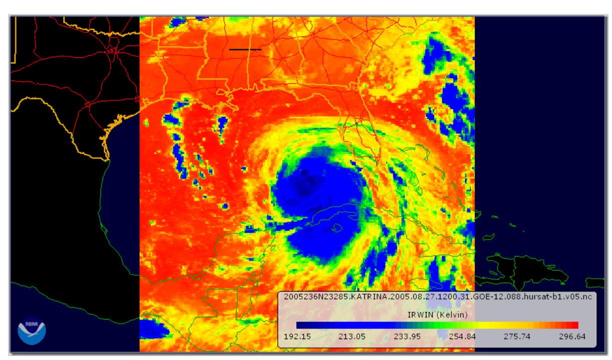

Figure 2: Sample query for Hurricane Katrina (2005)

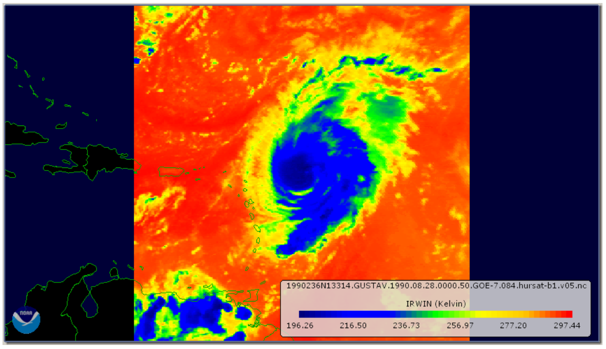

Figure 3: Nearest neighbor analog to Figure 2 from the training set, Hurricane Gustav, 28 August 1990.

100 kt. Figure 4 shows the similarity between the query and the NN in the 14 selected rings.

4. RESULTS

Several tests were done using *n*-fold cross-validation (usually referred as k-fold cross-validation) for statistical justification of the new technique. The distribution of the error is shown in Figure 5a. Error was defined as the absolute difference between reconnaissance-based measurements of intensity and the estimated value. Figure 5a can directly be compared to Figure 9 of Velden et al. (2006). The authors compared the Dvorak intensity estimates (for the period 1977-2003) with the best estimates of track intensity which were concurrent with aircraft reconnaissance; and found that 90%, 75% and 50% of their mean absolute errors were less than 18 kt, 12 kt and 5 kt respectively. In comparison, 90%, 75% and 50% of the absolute errors of this new algorithm were less than 18 kt, 14 kt and 10 kt respectively. Figure 5a clearly shows that the new technique has similar mean absolute error for 90% of the estimates and a much lower maximum absolute error (27 kt) as compared to 42 kt of the Dvorak technique (Figure 9 of Velden et al., 2006). Moreover, the averaged MAE, RMSE, and bias

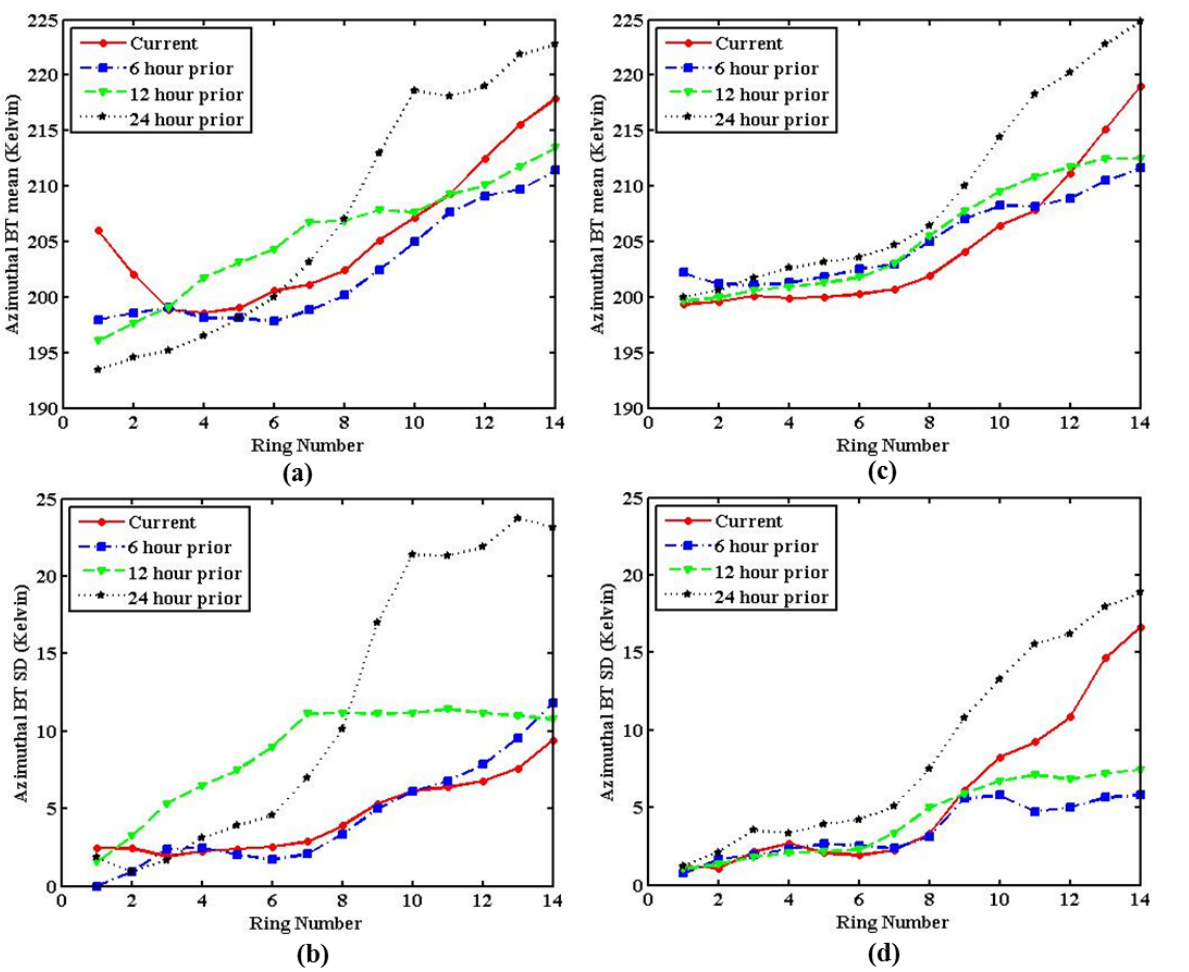

Figure 4: Azimuthal BT mean (a) and SD (b) for the 14 rings of the query image in Figure 2 (Hurricane Katrina, 2005) and nearest neighbor mean (c) and SD (d) from the training set (Hurricane Gustav, 1990).

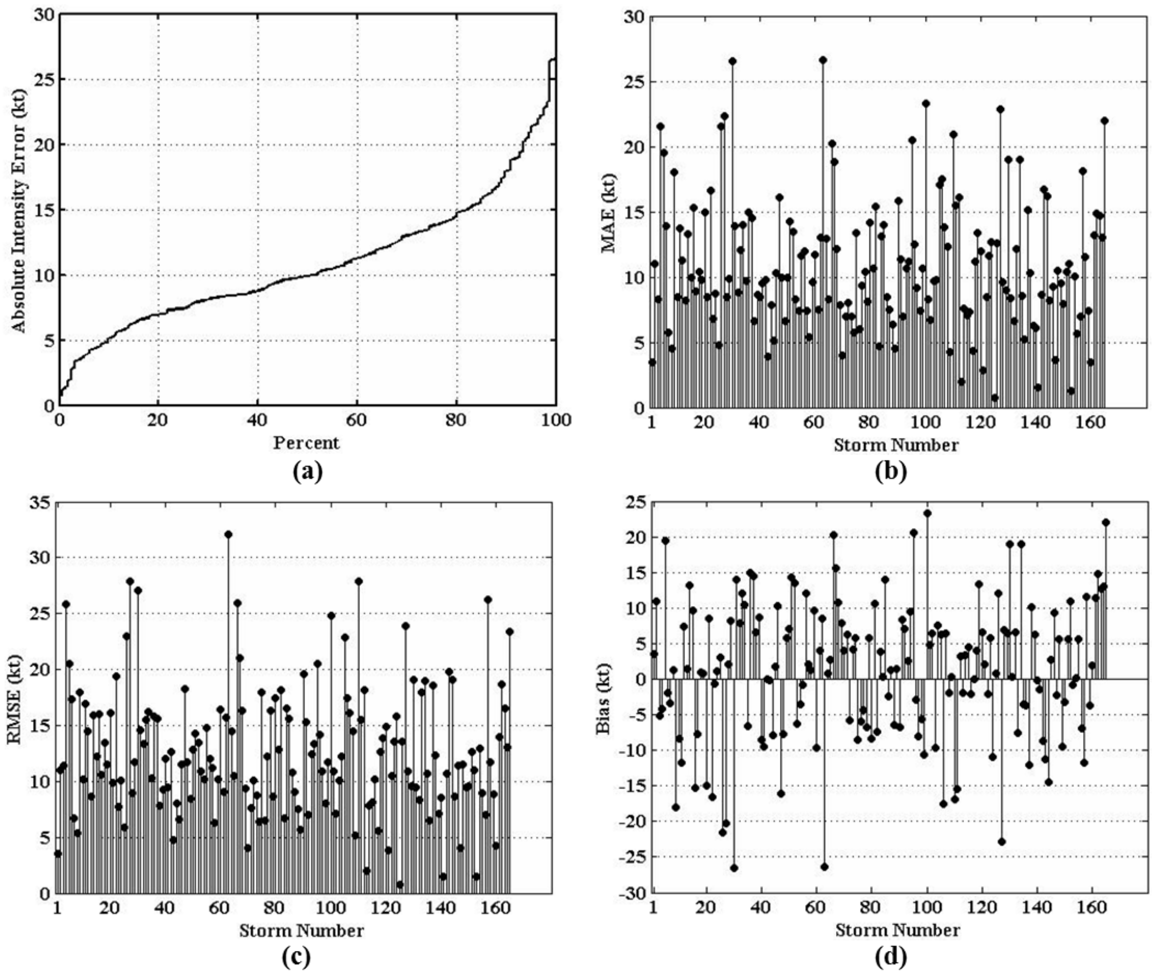

Figure 5: Cross-validation results using 165 storms in the Northern Atlantic from 1988 -2006 which were contemporaneous with the aircraft reconnaissance-based data for validation. (a) Distribution of the error (averaged MAE) for new method, (b) MAE, (c) RMSE, and (d) bias

of the new technique were 11 kt, 13 kt, and -1 kt respectively for all the 2016 samples of the storms. The term bias means the average differences between estimated values and the best track values which are concurrent with aircraft reconnaissance. The validation results for the 165 storms are shown in Figures 5b, 5c and 5d.

We present, in Figure 6, examples of estimation of intensity of the storms Allison (1995), Erika (1997) Floyd (1999) and Katrina (2005) based on our new estimation technique. These graphs show that the estimated values follow the best track (reconnaissance based data) values closely.

4.1 **Sensitivity Analysis of the Selected Parameters**

The number of similar images (K) used to estimate the intensity and the numbers of the rings around the center of storm were determined based on their effect on the average changes in the values of MAE and RMSE. This is done by changing the values of K and the ring number from 1 to 200 and 1 to 70 respectively and choosing the parameters with the minimum error values in *n*-fold cross validation. Variation of averaged MAE and RMSE are shown in Figure 7. Based on these variations, values for parameters were selected as K equal to 10 and the number of the rings as equal to 14. These 14 rings are 14 consecutive rings (5km, 15km,…, 135km) from the TC’s center.

5. SUMMARY AND FUTURE WORK

A technique for estimating intensity has been described, in which maximum sustained wind speed was estimated from analogs of storm imagery. The new image analysis used the *current* and preceding 6, 12 and 24 hours’ infrared satellite snapshots of TCs along with *duration* (*age*), as predictors of the expected intensity. Instead of regression techniques, the intensities of 10 closest analogs (determined using a

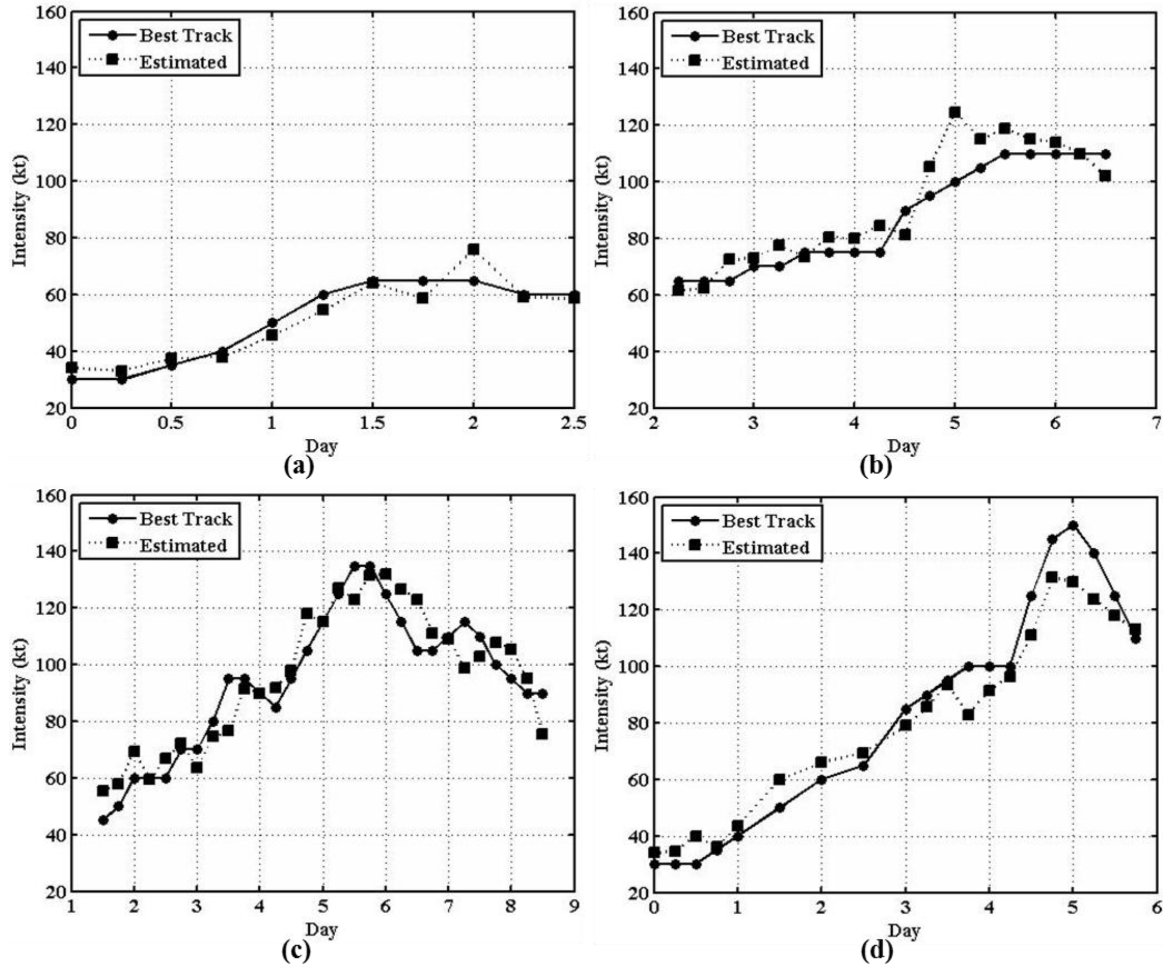

Figure 6: Best track (reconnaissance based data) and estimations using the new technique for (a) storm Allison (1995, MAE= 3.86 kt) (b) storm Erika (1997, MAE= 6.97 kt) (c) storm Floyd (1999, MAE= 7.46 kt) (d) storm Katrina (2005, MAE= 7.91 kt)

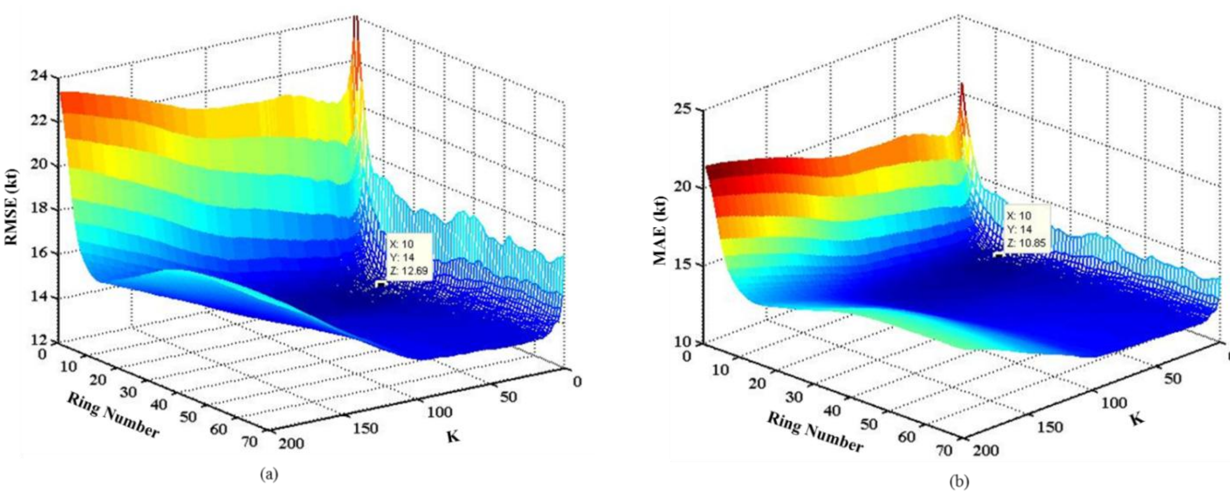

Figure 7: Variations of the average (a) RMSE and (b) MAE versus K and ring number

K-nearest-neighbor (K-NN) algorithm) were averaged to estimate the intensity. Several tests were implemented to statistically justify the new algorithm using *n*-fold cross-validation. The resulting average MAE is 11 kt (50% of points are within 10 kt). Moreover, the averaged MAE, RMSE, and bias of the new technique were 11 kt, 13 kt, and -1 kt respectively for all the 2016 samples of the storms.

New technique's accuracy is parallel with current objective techniques. The new technique also can be considered as a fully automated system which requires no human input except for the selection of the center of the circulation in the image. That is, the new algorithm could process a set of TCs' images based solely on imagery and the age of the cyclone. Thus, the system could produce regular estimates of the TC's intensity, for a given disturbance location, independent from any human interpretation. A fully automated processing system could be developed using automated system center techniques, such as those from Wimmers and Velden (2010).

Future work to improve the technique could include adding temporal constraints on the estimated intensity and increasing the number of training samples at higher intensities. Nonetheless, the simplicity, objectivity and consistency of our approach make it an important tool for estimating tropical cyclone intensity.

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Disclaimer

The opinions expressed in this paper are those of the authors. They do not necessarily reflect the official views or policies of NOAA, Department of Commerce, or the US Government.

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