OBJECTIVE, AUTOMATIC TRACKING OF PRE-GENESIS TROPICAL DISTURBANCES WITHIN THE DEVIATION ANGLE VARIANCE METHOD

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1. INTRODUCTION

The National Hurricane Center defines a tropical cyclone as a warm-core non-frontal synoptic-scale cyclone, originating over tropical or with organized subtropical waters. deep convection and a closed surface wind circulation about a well-defined center (NHC 2014). Because these intense, convective systems form in regions where it is challenging to obtain direct measurements, satellite-based methods have been developed to monitor their progress. The deviation angle variance (DAV) technique was introduced by Piñeros et al. as an objective method to estimate the intensity of a tropical cyclone (TC) from infrared (IR) satellite imagery (Piñeros et al. 2008; Piñeros et al. 2011; Ritchie et al. 2012) and the methodology is discussed in detail elsewhere (Piñeros et al. 2008; Piñeros et al. 2011; Ritchie et al. 2012).

More recently the DAV method was extended to assist in identifying tropical cyclogenesis (Piñeros et al. 2010). For this latter application, a map of DAV values is created using every pixel in the satellite image, one at a time, as the selected center for the calculation and then mapping the DAV value back to that pixel. The resulting map is then analyzed to find regions with DAV values below a pre-determined threshold, which indicate regions of high symmetry where a TC may be developing. The application of this method to the North Atlantic basin has produced excellent results with median TC detection times just ahead (0.6-3 hr) of the first indication of a tropical depression (TD) in the operational centers' retrospective besttrack archives depending on the DAV threshold used (Piñeros et al. 2010).

To enable the transition of the DAV method to a real-time operational forecast environment, it is necessary to keep track of potentially developing cloud clusters in IR satellite images between synoptic times when the operational fixes are not available. Objective methods such as centroid locations, location of minimum DAV, etc., may be used to obtain a center fix estimate for a given cloud cluster in an IR image. Unfortunately, these objective methods do not necessarily provide a robust way to keep track of a given disturbance (Piñeros 2009; Rodríguez-Herrera et al. 2014).

In this work, we present a shape analysisbased, objective, automatic tracking method that uses the DAV information to track the position and evolution of potentially developing cloud clusters within the DAV system. This method provides the framework for transforming the DAV technique into a fully automated, real-time system for identifying tropical cyclogenesis. The main objective of the work presented herein is to keep track of potentially developing cloud clusters and create a DAV cloud cluster evolution history before the actual genesis of a TC, simplifying the use of the method in operational centers.

2. DATA

The data used in this study include hourly Japan-based Multi-functional Transport SATellite MTSAT IR images at 10.7 µm from 2009-2012. The nominally 4-km/pixel IR images are remapped to a 10-km/pixel resolution before being processed using the DAV method (Piñeros et al. 2010) to produce maps of the DAV parameter, which correspond directly to the cloud patterns in the original IR image (Fig. 1).



Figure 1. DAV map of a region within the western North Pacific with a detection indicated (blue dot) on

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September 2, 2010 at: a) 0632 UTC; and b) 0732 UTC. The corresponding IR images are shown in c) and d).

In addition, invest and best-track databases from the Joint Typhoon Warning Center (JTWC) are used for validation of the automatic tracking routine.

3. AUTOMATIC STORM TRACKING

The objective, automatic tracking method uses information from both the original brightness temperature satellite image and its corresponding DAV map. Figure 2 is a flowchart with the main steps in the method. The satellite IR images used in this analysis were converted to an 8-bit digital format using an analog-to-digital conversion algorithm to facilitate the computation of the DAV maps. Using this set of data, the tracking system first looks for regions on the DAV map with a variance below a given threshold TH_{max} . The choice of TH_{max} was obtained from the receiver operating characteristic (ROC) curve computed in Piñeros et al. 2012, which plots positive detection of pre-genesis cloud clusters versus a false-alarm rate for particular DAV values. According to the ROC curve, a value of $TH_{max}=2000 \text{ deg}^2$ identifies 100% of the cloud clusters that might develop into TCs, albeit with high false alarm rates. Next, the tracking system locates pixels with locally minimum DAV values and compares those pixels to the corresponding IR image to verify that clouds likely associated with a weather disturbance of interest are present. This step is necessary as the DAV map solely contains symmetry information, and can find high symmetry in clear sky regions. The automatic tracking system defines a cloud cluster by computing the average brightness temperature within a region with radius R_{cloud} centered on the minimum DAV point and compares it with a user-defined threshold THB_{min}. Initially, the value of THB_{min} was chosen to be the 8-bit equivalent of 273.15 K (~147) as obtained from the MTSAT-2 calibration table http://mscweb.kishou.go.jp/operation/calibration/mt 2/HRIT/mt2 hrit 20100315.htm. A typical TC radius of 250 km was used as the value of R_{cloud}. Although TCs vary considerably in size, the chosen typical radius is a reasonable starting point. Regions with a minimum DAV below TH_{max} and an average brightness temperature greater than THB_{min} are labeled as detections, assigned a number, and included in a list that contains the

minimum DAV, the latitude and longitude of the point, and the detection time.

If either of the two thresholds is not reached, the point of minimum DAV is labeled as ghost detection, and the automatic tracking system checks the detections table for a previous detection that might have been found inside a



Figure 2. (Color online) Flowchart with the main steps of the objective, automatic tracking method. Details on a number of validations have been omitted to simplify the chart. The dashed rectangles enclose the detections that are labeled as either ghost, positive, or true detections.

circle of radius R_{track} centered on the ghost detection within a time period T_{track} . The value of R_{track} was chosen as the maximum radius previously used in genesis studies (Ritchie et al. 2012), namely 500 km, and is consistent with the distance a cloud cluster would have propagated on average within the time T_{track} (initially set to 24 hours). Ghost detections are used to follow cloud clusters that are potentially of interest in the event

that no actual detection is found over an extended period of time T_{track}. If no previous detection satisfying both conditions is found in the detections table, the ghost detection is dismissed. Otherwise, the tracking system upgrades the ghost to a full detection and includes the cluster information for that time in the detections table. This is an important step because a cloud cluster being tracked might lose symmetry at some stages of its early evolution, but later reorganize and continue developing. If either no detection associated with a previous detection is found within a time period T_{track} or the average brightness temperature falls below THB_{min}, the cloud cluster is considered to have dissipated. Any new detection in the vicinity is labeled as a new cloud cluster and tracked as described above.

The TH_{max} DAV value used to identify detections produces realistic TC durations in comparison with those reported in the best-track database. However, using this value as the threshold for true detections, i.e., cloud clusters that have the potential to develop into TCs, produces a large number of false positives (Piñeros et al. 2010). Therefore, a lower DAV value, TH_{true}, is used to indicate true detections and generate a second table that contains the corresponding cluster information. The value TH_{true} =1750 deg² was chosen for this study from the ROC curve in Piñeros et al. 2012 because it yields a true positive rate greater than 95% with a false positive rate (FPR) of less than 25%. In addition, this value yields a median time of detection approximately equal to the designation of a TC as a TD in the best-track archive in both North the Atlantic available from http://www.nhc.noaa.gov/data/#hurdat and the western North Pacific available from http://www.usno.navy.mil/NOOC/nmfc-

ph/RSS/jtwc/best tracks/wpindex.html. A strategy to further reduce the FPR was implemented in the tracking system using the cumulative time that a potentially developing storm spends below TH_{true} . The minimum cumulative time to consider a cloud cluster as an actual true positive, T_{true} , was chosen to be a full diurnal cycle. Furthermore, a land mask was applied to initial detections, since cloud clusters originating over land rarely develop into TCs. However, subsequent detections over land of an already identified cloud cluster of interest are retained. The combination of these two criteria resulted in no false positives detected in the shortterm analysis discussed below. In real-time genesis analyses, the value of T_{true} can be reduced to only a few hours (e.g., 3–5 hours) in order to avoid delaying the detection time by a full diurnal cycle. However, the reduction of the detection time delay comes at the expense of a higher FPR.

Figure 3 is a snapshot of the automatic tracking system with six identified cloud clusters being tracked and two dissipating TCs that are still being tracked. The circles in the image are centered on the current detections and color coded to distinguish between new detections (blue), previously identified detections (green), and ghost detections (yellow). The eight sets of dots represent the current and previous locations of each cloud cluster with time latency T_{track} . Different colors have been used to mark each identified cloud cluster. The size of each is a function of the DAV value for each detection: large dots correspond to low DAV values and small dots to high DAV values. Two TCs shown in Fig. 3, Lionrock (19.4N, 118.1E, current intensity = 50.0 kt, dark brown dots) and Kompasu (28.4N, 126.6E, current intensity = 102.9 kt, light brown dots), were included in the 2010 best-track database from the JTWC.



Figure 3. (Color online) Snapshot of the automatic tracking system with two dissipating TCs that were previously tracked and 6 identified cloud clusters being tracked in the western North Pacific basin on August 31, 2010 at 2132 UTC. The color-coding distinguishes between new detections (blue), previously identified detections (green), and ghost detections (yellow).

4. TUNING THE METHOD

The automatic tracking method was tuned by comparing its performance with consensus results obtained manually from a subjective blind test by two operators. Each operator analyzed a set of 262 hourly IR brightness temperature images of the western North Pacific basin between August 25, 2010 at 0032 UTC and September 5, 2010 at 2332 UTC. A total of 26 nonconsecutive hourly IR images were missing from the data set. The operators in this case were postdoctoral researchers in our group with extensive experience in TC analysis. Cloud clusters were tracked and the location and minimum DAV values were recorded. Because there were minor differences between the resulting analyses, a subjective consensus was formed. The results from the subjective analysis were compared to the results from the automatic system, and some parameters (TH_{max}, TH_{true}, R_{cloud}, THB_{min}, R_{track}, and T_{track}) were calibrated to ensure that the automatic results match the manual results within a radius of 5 degrees and a time of detection of 6 hours. The majority of parameters had little or no effect on the performance of the method when varied by less than 10% of their initial value. The only exception was THB_{min}, for which a small variation enabled a better match with the subjective results.

Table I shows the start and finish date/time reported by the automatic tracking using the TH_{max} threshold. The time difference $\Delta \tau_1$ is the duration of the storm from the first time that the DAV value falls below TH_{max} until the last time that it is below that value. The differential $\Delta \tau_2$ is the time difference between the first and last time that the DAV falls below TH_{true}, i.e., the duration obtained by the automatic tracking system that corresponds to the duration reported by the manual test. The comparison between the automatic tracking and manual test reported latitude, longitude, start time, and finish time and showed that these were exactly the same for most storms, with the exception of the finish time reported for cloud clusters 2 and 3 discussed below. The perfect agreement between the latitude and longitude of the cloud clusters is to be expected, since they correspond to those of the point with minimum DAV within a circular region of radius R_{track} . The

differential $\Delta \tau_{12}$ is the time difference between the first time that the DAV value falls below TH_{max} and the first time that it falls below TH_{true} . The TC names reported in the table are the names assigned to true positives by the JTWC.

All of the manually detected cloud clusters have a corresponding cloud cluster detected by the automatic tracking system. The assigned numbers do not coincide between the manual and automatic tracking, except for the first part of the first cloud cluster and second cloud cluster, because the total number of cloud clusters detected in each case is different. In most cases, the start and finish date and time used to compute $\Delta \tau_2$ coincide perfectly between the manual and automatic tracking, as shown in Table II. Two exceptions are cloud clusters 2 and 3 (Lionrock and Kompasu, respectively) from the automatic tracking system, which detected the last time the DAV value was below TH_{true} up to 17 hours after the end of the cloud cluster recorded on the manual test. This shows the high sensitivity of the automatic system to track even vanishing cloud clusters. Furthermore, cloud cluster 2 on the automatic results was identified by the automatic tracking system as a potentially developing TC 6 hours in advance of the manual test (see Table I).

An important issue observed in the results of the automatic tracking is the split of the storm labeled by the system as cloud cluster 1, which was identified on the manual test as cloud clusters 1, 3, and 5. This tracking mismatch is due to the complexity of the cloud cluster that developed into Tropical Storm (TS) Namtheun. Its average brightness temperature fell just below *THB_{min}* and its DAV value rose just above *TH_{max}* at intermediate stages of its development. This is a tricky case that was difficult to identify as a single cloud cluster on the test because that particular cloud clusters that later developed into TS Lionrock and Typhoon Kompasu.

Storm Name	Start Date/Time (UTC)	Finish Date/Time (UTC)	Δτ ₁ (Hrs.)	Δτ ₂ (Hrs.)	Δτ ₁₂ (Hrs.)	Storm Number	
						Man. Tracking	Auto. Tracking
Namtheun	08/25 – 0032	08/30 – 2332	143	119	21	1, 3, 5	1
Lionrock	08/28 – 0732	09/02 – 2232	135	124	1	2	2
Kompasu	08/27 – 2032	09/01 – 2332	123	107	16	4	3
Malou	08/31 – 2132	09/05 – 2332	122	49	73	6	4

Table I. List of true positive detections obtained from the blind test after consensus and the objective, automatic tracking system. The storm numbers listed in each column correspond to the numbers assigned by either the manual tracking or the automatic tracking system. In the majority of the detections, the start and finish time/date and latitude/longitude were exactly the same in the manual and automatic tracking, even for detections that did not develop into TCs. The only two exceptions are the true positive detections with number 2 and 3 from the automatic tracking system. These two detections are further discussed in Section 4.

Storm Name	Start Date/Time (UTC)		Finish Date/Time (UTC)			
	Man. Tracking	Auto. Tracking	Man. Tracking	Auto. Tracking		
Namtheun	08/25 – 2132	08/25 – 2132	08/30 – 2032	08/30 – 2032		
Lionrock	08/28 – 0832	08/28 – 0232	09/01 – 2032	09/02 – 1232		
Kompasu	08/28 – 1232	08/28 – 1232	09/01 – 1832	09/01 – 2332		
Malou	09/03 – 2232	09/03 – 2232	09/05 – 2332	09/05 – 2332		

Table II. Comparison between the start and finish date/time of the true positive detections obtained from the blind test after consensus and the objective automatic tracking system. These results report the first and last time that the DAV value was below TH_{true} and were used to compute $\Delta \tau_2$ and $\Delta \tau_{12}$ in Table I.

5. PERFORMANCE IN LONG-TERM TRACKING

Once the automatic tracking system was tuned to reproduce the results from a manual analysis for a 12-day period, its performance was tested using 4 years of best-track and invest data from JTWC in the western North Pacific encompassing 2009-2012. The test was limited to 52% of the disturbances in the JTWC archives because of the lack of availability of some IR imagery in our database. Other basins were not included in this study. Nevertheless, due to the high complexity of the disturbances in the western North Pacific, we expect the results obtained in this basin to be representative of the performance of our method. The number of disturbances reported by the JTWC and our tracking method, including best-track and invests, for which enough IR imagery is available in our archive to enable the tracking analysis are shown in Table III. Almost all TCs in the best-track archive for which we have data available were detected and successfully tracked by the tracking system, with a maximum location difference between best-track entries and tracking system detections of 5 degrees in latitude and longitude within a time difference of 6 hours, i.e., the time intervals at which the best-track and invests are recorded. In this context, we consider that IR data is available for a particular period if the time between succeeding images is shorter than T_{track} . In the case of invests, many disturbances for which we have data available were successfully identified and tracked by the automatic system. The rest of them were very weak and did not produce a DAV signal low enough to reach the TH_{max} threshold. This property of the automatic tracking method can be used to discriminate invests with potential to develop from those that are highly unlikely to develop. A number of disturbances detected by the tracking method using the TH_{max} threshold do not have a counterpart in the invest archive and constitute false positive detections that do not reach the TH_{true} threshold or do it for a period shorter than T_{true} . The number of disturbances identified by the automatic tracking method that correspond to disturbances in JTWC's best-track and invest archives are also shown in Table III.

Tracking System	JTWC		Auto	Tracking	# That Correspond	
Season	# Develop.	# Non- develop.	# Develop.	# Non- develop.	# Develop.	# Non- develop.
2009	23	44	23	49	23 (100%)	15
2010	19	77	17	49	17 (89%)	15
2011	20	44	19	30	19 (95%)	7
2012	20	29	16	23	16 (80%)	8

Table III. Number of developing and non-developing disturbances reported by the JTWC and detected by the objective, automatic tracking method during each season of the 4-year period 2009–2012. Some perturbations detected by our method were split in two or three different perturbations. This issue is discussed in Section 5. Only disturbances for which enough IR imagery is available in our archive to enable the tracking analysis were included in the long-term validation of the method.

Approximately 30% of the disturbances in the JTWC's best-track and invest files were detected as two or three different disturbance by the automatic tracking system. We have identified three classes of disturbances that present this issue. The first class is comprised of disturbances that form in the South China Sea. These disturbances often have large cloud bands far from, yet associated with, the central circulation. However, the automated tracking system has difficulty connecting them together. The close proximity of land complicates the process. The second class is constituted by systems that undergo extratropical transition. Because these systems rapidly accelerate they require different internal settings of R_{track} and T_{track} than the main set of cases and are beyond the scope of this work. Finally, the third class is constituted by invests identified by the JTWC that are not easily tracked using IR imagery alone, making them problematic for the automated tracking system.

Because of the large amount of data produced for the 4-year comparison between the objective, automatic tracking method and JTWC's tracking files, it is impractical to present the results of the comparison here. However, the data set can be obtained by contacting the corresponding author. In general, the coincidence between the JTWC's tracking files and the results of the automatic tracking method is extremely close, although not perfect. One issue in particular was that in the event of a temporary satellite shutdown, or other reason for loss of images, human intervention was necessary to re-align the tracked cloud clusters.

6. CONCLUSIONS

An automated cloud cluster tracking system based on the DAV has been presented. A 12-day comparison with a manual analysis was used to tune the automatic technique. Finally, the technique was compared with 4-year of invest and best-track data from the JTWC in the western North Pacific.

The results presented in this work show that the performance of the objective, automatic tracking method is comparable to that of a manual analysis in both long- and short-term tracking analyses. The method provides an objective estimation of the location of a cloud cluster that can be used to create a pre-genesis history of both developing and non-developing storms. This history may be used to identify features of developing tropical disturbances during their early stages of development and separate them from cloud clusters that are clearly non-developing. Although this is a limited sized dataset, preliminary work in other basins does appear to corroborate the findings presented here. While the automatic tracking system has been designed to work with the DAV genesis technique (Piñeros et al. 2010), it can also be used to: initially locate all existing cloud clusters; filter them for only those cloud clusters with potential to continue developing; and report those filtered cloud clusters continuously to a database, relieving the forecaster of much manual work. Current work includes: 1) testing the automatic tracking technique in the eastern North Pacific basin in conjunction with the genesis DAV technique; 2) and using the built-in capabilities of the automated system to develop the probabilistic genesis DAV technique.

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