Cyclone Tracking using Multiple Satellite Data Sources via Spatial-Temporal Knowledge Transfer

Shen-Shyang Ho and **Ashit Talukder**
Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Ave 300-123
Pasadena, CA 91109

Abstract

To track a cyclone using a single orbiting satellite in a continuous manner is impractical as it has limited spatial and temporal coverage. One solution is to use multiple orbiting satellites for cyclone tracking. However, data from some orbiting satellites do not provide features as useful as other satellites in identifying cyclones. Moreover, satellite data containing strong cyclone discriminating features is affected by coarse temporal resolution and object occlusion while satellite data containing weak cyclone features does not have positive examples for cyclone identification. In this paper, we propose a methodology for spatial-temporal knowledge transfer to enable cyclone identification and detection using data with weak features in a multiple data sources setting. This approach also minimizes the negative effect of coarse temporal resolution and occlusion when only the satellite data containing strong cyclone discriminating features is used. Experimental results are presented to demonstrate the feasibility and usefulness of our knowledge transfer approach for cyclone tracking.

Introduction

Tropical and extra-tropical cyclones are important components of the Earth climate system that exhibit variability at different temporal and spatial scales. A cyclone landfall causes great devastation, incurs fatality, and affects people's livelihood. To identify and track tropical weather system, the Tropical Prediction Center/National Hurricane Center (TPC/NHC) uses conventional surface and upper-air observations and reconnaissance aircraft reports (Pasch, Stewart, and Brown 2003), and these are concentrated in the North American coasts and in Japan/Europe to some degree. Coverage on a global basis, especially in under-developed and developing nations such as large portions of Asia and Africa is limited or lacking which results in disastrous consequences in many of these regions. In recent years, some studies have used satellite images that are manually retrieved and analyzed to improve the accuracy of cyclone tracking; this procedure is currently slow, tedious, involves coverage of only local regions in North America, and requires close analysis by teams of experts.

Satellite sensor data from the QuikSCAT (Quick Scatterometer) mission providing wind speed and direction measurement has been extremely powerful in identifying a cyclone which is an "organized deep convection and a closed surface wind circulation about a well-defined center"[1] of high sustaining wind speed. Recent research showed that QuikSCAT data could be useful in early identification of tropical depression (Katsaros et al. 2001) and early detection of tropical cyclones (Pasch, Stewart, and Brown 2003; Sharp, Bourassa, and O'Brien 2002). Moreover, QuikSCAT data has been used in the three-dimensional variational data assimilation technique for better cyclone tracking and intensity forecasting (Liang et al. 2007). Our recent work (Ho and Talukder 2008) showed the feasibility of using QuikSCAT wind measurements for automated cyclone identification. However, due to the polar orbiting nature of the QuikSCAT satellite, it has limited spatial and temporal coverage. In particular, the time interval between two consecutive observations of a cyclone is approximately around 12 hours. Sometimes the sensor can only capture partial measurement of the cyclone due to the orbiting path. To alleviate these problems, one can use sensor measurements from multiple orbiting satellites. However, the sensors from other satellites measure other earth and atmospheric properties. These measurements are not as powerful in identifying cyclone as the wind properties measured by the Scatterometer on QuikSCAT satellite. For example, the precipitation rate measured by the Tropical Rain Measurement Mission (TRMM)[2] has been used to trace the cyclone track manually either during a cyclone event or as a reanalysis after a cyclone event. However, the precipitation rate cannot be used for cyclone identification since heavy rainfall does not imply a cyclone event. Moreover, since precipitation rate is not a definite cyclone indicator, there is no archival of positively labeled (cyclone) examples from the TRMM data by the scientific community.

In this paper, the main contribution is a methodology for transferring local spatial-temporal knowledge between satellite data from different data sources to enable event detection using weaker features. To avoid negative transfer for our methodology, the assumption that the weaker feature,

[1] http://www.research.noaa.gov/weather/t_hurricanes.html
[2] http://trmm.gsfc.nasa.gov/

which is not a definite discriminating feature, has to be able to pick up the event of interest must be satisfied. In other words, without applying our methodology, using the weaker feature for object detection/identification should result in a high false positive rate and high true positive rate, i.e. low precision but high recall. This methodology also results in minimizing the negative effect of coarse temporal resolution and event occlusion in cyclone tracking.

The paper is organized as follows. In the next section, we describe in detail the problem of applying knowledge transfer for cyclone detection using multiple satellite data sources. Then, we describe our methodology for spatial-temporal knowledge transfer. After that its application to cyclone detection is described in detail and we demonstrate the feasibility and usefulness of our approach to cyclone tracking. Before the conclusion, we discuss some future work.

Spatial-Temporal Knowledge Transfer

Inductive transfer or transfer learning refers to “the problem of retaining and applying the knowledge learned in one or more tasks to efficiently develop an effective hypothesis for a new task”.[3] The key characteristic of transfer learning is that knowledge is transfer across domains, tasks, or/and distributions that are similar but not identical. Transfer learning capitalizes on previously acquired domain knowledge or data model (from other problems) to benefit the handling of current related task.

The problem of using multiple data sources for a single target task can be studied in a general framework for transfer learning. For a classification problem, classifiers based on data from different sources perform differently. To improve classification performance, one could either combine/fuse data from multiple sources to create a richer knowledge representation or use an ensemble consisting of multiple classifiers.

For cyclone tracking, one has the additional time and space constraints on the data from multiple satellite sources. In other words, a satellite data matrix from source A is collected at time t_1 on some cyclone event in region R_1 while the next data from source B is collected at time t_2 on the same cyclone event in region R_2 such that $t_1 \neq t_2$, $R_1 \neq R_2$ and $Area(R_1) \neq Area(R_2)$ since cyclone is a dynamic event (see Figure 1). Hence, one could not simply merge/fuse/combine data from source A and B.

We introduce the concept of spatial-temporal knowledge transfer to overcome the issues related to using multiple data sources for (near) real-time object tracking. In Figure 2, we give a high-level view of the concept of spatial-temporal knowledge transfer from Detector A built using training data with more discriminating power (QuikSCAT) to detector B which uses the spatial-temporal knowledge from Detector A and prior knowledge from data with lesser discriminating power (TRMM) for cyclone tracking. To avoid negative transfer that would result in poor detection and tracking performance, two conditions need to be met:

1. Detector A built using training data with more discriminating power must be as powerful as possible so that the spatial-temporal knowledge generated is useful for the weaker Detector B.
2. The much weaker Detector B should have a high true positive rate (i.e., high recall).

A high false positive rate (i.e., low precision) for Detector B does not affect the performance of tracking as long as accurate spatial-temporal knowledge is available from Detector A.

[3] NIPS 2005 Workshop “Inductive Transfer : 10 Years Later”

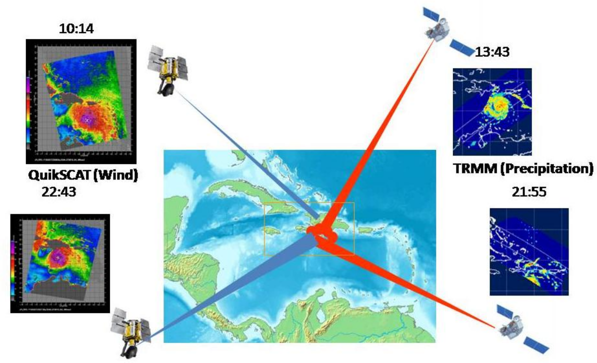

Figure 1: Data from multiple satellite data sources e.g. the QuikSCAT and the TRMM satellites for cyclone tracking

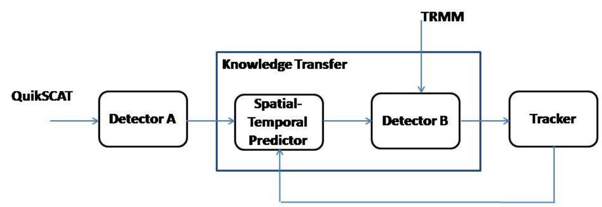

Figure 2: Spatial-temporal Knowledge Transfer between the TRMM data source and the QuikSCAT data source for cyclone tracking.

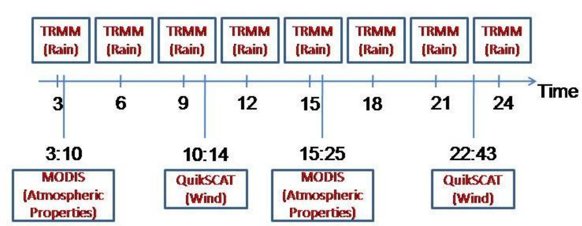

Figure 3: Data availability timeline for TRMM (3B42 data), QuikSCAT (L2B data) and Aqua (MODIS) on 18 Aug 2007 for Hurricane Dean

Spatial-temporal knowledge transfer enables the application of TRMM data for automated cyclone tracking which was previously not possible. One direct effect of using multiple satellite data sources is a reduction in the temporal resolution of observing two consecutive cyclone event images from about 12 hours using a single QuikSCAT satellite to a maximum of 3 hours using TRMM and QuikSCAT (and also the Aqua) satellites (See Figure 3). More information about the QuikSCAT and TRMM data is found in the Appendix.

In the next section, we describe our spatial-temporal knowledge transfer methodology in detail.

Methodology

The spatial-temporal knowledge transfer methodology is driven by a Kalman filter (Welch and Bishop 2006). At initialization, spatial-temporal knowledge is extracted from the data source with strong discriminating features for object tracking. This knowledge is used by the weaker detector to localize the search region for detection. After the object is detected, adjustments are made to the spatial-temporal knowledge. It is used for the next search region prediction together with spatial-temporal knowledge extracted from the strong detector (see Figure 4).

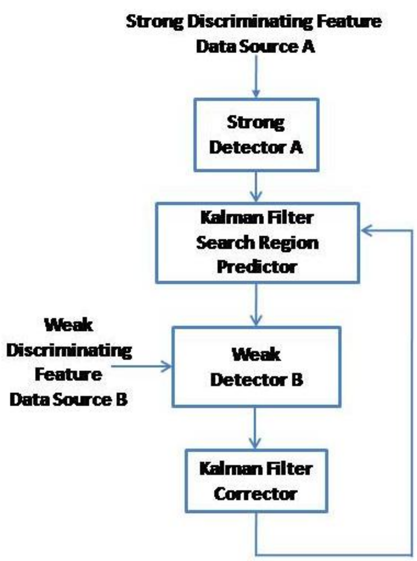

Figure 4: Spatial-Temporal Knowledge Transfer between data sources containing strong and weak features

The system equations used in the Kalman filter are

$$x_{k+1} = A_{k+1}x_k + w_k z_k = H_k x_k + v_k$$

where x_{k+1} is the state vector at time instance $k+1$, z_k is the observation vector at time instance k, A_{k+1} is the state transition matrix, H_k is the observation matrix, w_k and v_k are Gaussian noise at time instance k. The matrix form of the above system equations are as follows.

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \Delta x_{k+1} \\ \Delta y_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & \Delta t_{k+1} & 0 \\ 0 & 1 & 0 & \Delta t_{k+1} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ \Delta x_k \\ \Delta y_k \end{bmatrix} + w_k$$

$$\begin{bmatrix} \hat{x}_k \\ \hat{y}_k \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ \Delta x_k \\ \Delta y_k \end{bmatrix} + v_k$$

where Δt_{k+1} is the time difference between the next satellite image at instance $k+1$ and the current satellite image at instance k. Δx_k and Δy_k are the approximated x-y component speeds of the predicted cyclone at instance k. One notes that the speed approximation Δx_{k+1} and Δy_{k+1} at instance $k+1$ is based on the time difference and distance traveled by the cyclone from instances $k-1$ to k.

This knowledge transfer process continues as one tracks the object with two data sources, one with weak features and one with strong features. This knowledge transfer process can be further generalized to the two following scenarios:

1. Multiple data sources with either strong or weak discriminating features, and
2. Occurrence of consecutive strong/weak feature observations.

The knowledge transfer process shown in Figure 4 can be easily extended to Scenario 1. For Scenario 2, knowledge transfer can be ignored when there are consecutive strong feature observations. However, when there are consecutive weak feature observations, one needs to use the previous weak feature observation to make search region prediction for the next weak feature observation. A combination of Scenario 1 and 2 is shown in Figure 3. In our current implementation, cyclone tracking occurs in Scenario 2. We note that the tracking performance is not affected as long as a strong feature observation is measured within a reasonable number of weak observations. We point out here again that in our cyclone tracking problem weak feature observations are more readily available and it helps to reduce the temporal resolution of cyclone tracking.

Experimental Results

Our knowledge transfer solution leverages the strength of each remote sensor type for cyclone tracking. QuikSCAT wind measurement has excellent information for accurate cyclone detection but lacks sufficient temporal resolution (each pass-through is repeated every 12 hours). TRMM precipitation measurement on the other hand has excellent temporal resolution of 3 hours, but lacks good discriminative ability for accurate cyclone detection. Therefore, we employ (strong feature) QuikSCAT wind measurement for cyclone detection (every 12 hours), and knowledge transfer to (weak feature) TRMM precipitation measurement for detection/tracking (every 3 hours). This solution therefore ensures a high detection rate for cyclones while maintaining fine temporal resolution during cyclone tracking.

Our automated cyclone tracking uses spatial-temporal knowledge transfer shown in Figure 4 under Scenario 2 described in the previous section. Initially, QuikSCAT data is retrieved from the database or from real-time streaming information, and is input into the Strong Detector A, an improved version of the cyclone identification system (Ho and Talukder 2008), to locate/identify possible cyclones. The cyclone location is then used to predict the regions that are likely to contain a cyclone at the next incoming data stream retrieved using a linear Kalman filter predictor. If the next data stream is the TRMM data, a constrained search is carried out around the region most likely to contain the cyclone as identified by the Kalman filter predictor. This constrained tracking via the Kalman filter predictor is especially important for the TRMM precipitation data as it is not a definitive indicator of cyclones and is susceptible to high false alarms. The estimated search region localizes the region that is most likely to contain cyclone based on past cyclone tracks and hence the incidence of false alarms is minimized by a large margin. A cyclone is localized by applying a threshold to the TRMM precipitation rate measurement (Weak Detector B). After a cyclone is located in the TRMM data, the Kalman filter measurement update ("correction") is applied to obtain an estimate of the new state vector or the predicted location of the cyclone in the next TRMM (or QuikSCAT) observation cycle after 3 hours. The Δt_{k+1} in the system equation in the Kalman filter is a known parameter between two consecutive TRMM satellite images (3 hours), and between a current QuikSCAT image and the next TRMM satellite image.

A cyclone is a dynamic event and its size evolves rapidly over time. Typical tracking and prediction techniques use the center of an object as the single point to track and predict over time. This model works well for rigid objects that do not change shape with time. However, modeling and predicting the evolution of a cyclone in space over time using only the cyclone center will be grossly inadequate since cyclones often increase in size as they evolve from a depression to a storm to a hurricane, and then decrease rapidly in size after hitting landfall. We therefore model the cyclone as two four-dimensional state vectors that described the maximum and minimum latitude/longitude of the bounding box spanned by the cyclone. Our hypothesis is that the bounding box that is described by the (x, y) spatial span of the cyclone evolves linearly in space over time. We expand (or contract) the estimated bounding box based on the estimated Kalman error covariance to define a search region for the cyclone in the TRMM image. This modeling approach significantly improves the quality of knowledge transfer between multiple satellite data sources as compared to using a predictor/tracker using only the center coordinates of the cyclone.

Figure 5 demonstrates the feasibility of tracking methodology using both Level 2B QuikSCAT data and 3B42 TRMM data (see Appendix) for Hurricane Isabel in North Atlantic Ocean for two days from a data sequence in 4-18 September 2003. We include the detection and tracking sequence for the 2007 Hurricane Gonu (reaching Category 5 wind speed level), the strongest tropical cyclone since record keeping begun in 1945 for the North Indian Ocean and the Arabian Sea, as additional material[4] to support our transfer learning methodology applied to cyclone tracking. Hurricane Gonu is an interesting event as tropical cyclones developed in the Arabian Sea very rarely exceed the tropical storm intensity (i.e., becoming a hurricane).

[4] http://shenshyang.googlepages.com/gonu.ppt

Future Work

Knowledge transfer between different satellites is a challenging and as yet unresolved problem, and an efficient solution such as ours that taps the information from such disparate sources will greatly improve science data understanding in various domains in environmental and space science. To date, we have tested our technique on isolated hurricanes. We aim to test our implementation over a longer time scale in a region where there are occurrences of multiple cyclones that will allow us to demonstrate the global tracking capability of our implementation.

In our current implementation, the merged TRMM 3B42 data are used for motion/location prediction and cyclone tracking. In the future, we would like to deploy (i) TRMM 2B25 swath data to construct a vertical profile of reflectivity for cyclone events to be in the constructing new strong detector. We plan to include the TRMM 3B40RT gridded data with an hourly temporal resolution (but with a poorer spatial resolution) to further improve the quality and accuracy of cyclone detection and tracking. Further knowledge transfer will also include the use of MODIS atmospheric data from the Aqua satellite and sensor measurements from other satellites to further refine the detection and temporal tracking accuracy.

Conclusion

Tracking cyclone using a single orbiting satellite in a continuous manner is impractical due to the limited spatial and temporal coverage. One solution is to use multiple orbiting satellites for cyclone tracking. We propose a spatial-temporal knowledge transfer methodology driven by linear Kalman filter that enables data with weak features to be useful for identification and detection. Spatial-temporal knowledge transfer enables the application of TRMM data for automated cyclone tracking which is previously not possible. One direct effect of using multiple satellite data sources is the reduction in the temporal resolution of observing two consecutive cyclone event images from about 12 hours using a single QuikSCAT satellite to a maximum of 3 hours using TRMM and QuikSCAT satellites.

Acknowledgement

This work was carried out at the Jet Propulsion Laboratory, California Institute of Technology with funding from the NASA Applied Information Systems Research (AISR) Program. The first author is supported by the NASA Postdoctoral Program (NPP) administered by Oak Ridge Associated Universities (ORAU) through a contract with NASA. The authors thank Andrew Bingham and Eric Rigor for their help in obtaining the Level 2B QuikSCAT data.

References

Ho, S.-S., and Talukder, A. 2008. Automated cyclone identification from remote quikscat satellite data. In *IEEE Aerospace Conference*.

Katsaros, K. B.; Forde, E. B.; Chang, P.; and Liu, W. T. 2001. Quikscat's seawinds facilitates early identification of tropical depressions in 1999 hurricane season. *Geophysical Research Letters* 28(6):1043–1046.

Liang, X.; Wang, B.; Chan, J. C.; Duan, Y.; Wang, D.; Zeng, Z.; and Ma, L. 2007. Tropical cyclone forecasting with model-constrained 3d-var. ii: Improved cyclone track forecasting using amsu-a, quikscat and cloud-drift wind data. *Q.J.R. Meterol. Soc.* 133:155–165.

Lungu, T., and et. al. 2006. Quikscat science data product user's manual. *Version 3.0, D-18053-Rev A*.

Pasch, R. J.; Stewart, S. R.; and Brown, D. P. 2003. Comments on "early detection of tropical cyclones using seawinds-derived vorticity". *Bulletin of the American Meteorological Society* 85(10):1415–1416.

Sharp, R. J.; Bourassa, M. A.; and O'Brien, J. J. 2002. Early detection of tropical cyclones using seawinds-derived vorticity. *Bulletin of the American Meteorological Society* 83(6):879–889.

Welch, G., and Bishop, G. 2006. An introduction to kalman filter. *TR 95-041, Department of Computer Science, University of North Carolina at Chapel Hill*.

Appendix

QuikSCAT Wind Data

The QuikSCAT (Quick Scatterometer) mission provides important high quality ocean wind data set. QuikSCAT is a polar orbiting satellite with 1800 km wide measurement swath on the Earth surface. Generally, this results in twice per day coverage over a given geographic region. The specialized microwave radar (SeaWinds instruments) on the QuikSCAT satellite measures wind speed and direction under all weather and cloud conditions over Earth oceans. Near real-time wind data is available to weather forecasting agencies from NOAA within three hours of observation. The ocean wind vectors in the measurement swaths have a spatial resolution of 12.5 and 25 km. The ocean wind data is used for global weather forecasting and modeling. It is also used to understand environmental phenomena such as El-Nino, tropical cyclones, and the effects of winds on ocean biology.

The SeaWinds Processing and Analysis Center (SeaPAC) at JPL is responsible for the reception of the telemetry data from the satellite, raw data processing and analyzing. The processed data is then delivered to the Physical Oceanography Distributed Active Archive Center (PO.DAAC)[5] for public distribution. PO.DAAC distributes Level 1B (time-ordered earth-located radar backscattering coefficient, σ), Level 2A (surface flagged σ and attenuations in 25 km and 12.5 km swath grid), Level 2B (ocean wind vectors in 25 km and 12.5 km swath grid) and higher level data products to the scientific users. Moreover, it provides long term archive for all telemetry, lower level and raw data collected from the QuikSCAT mission. More information about QuikSCAT science data product is found in (Lungu and et. al. 2006).

Near real-time (NRT) QuikSCAT satellite data is available for operational weather forecasting and modeling organizations. NRT QuikSCAT wind vector data needs to be ready for operational use within less than three hours from the earliest observations in a data pass. The data are provided to the Centers for Environmental Prediction (CEP), the European Centre for Medium-Range Weather Forecasts (ECMWF), and other meteorological agencies for use in marine forecasting, operational global numerical weather prediction, and climate forecasting. One notes that NRT QuikSCAT data are kept for only 14 days and no historical data are available. Hence, the Level 2B data which contains information similar to the NRT data is used in the development of our methodology.

TRMM Precipitation Data

The Tropical Rainfall Measurement Mission (TRMM) is a joint mission between NASA and the Japan Aerospace Exploration Agency (JAXA) designed to monitor and study tropical rainfall . The TRMM satellite carries five remote sensing instruments onboard, namely: Precipitation Radar (PR), TRMM Microwave Imager (TMI), Visible Infrared Scanner (VIRS), Clouds and Earth Radiant Energy Sensor (CERES), and Lightning Imaging Sensor (LIS).

TRMM satellite orbits between 35 degrees north and 35 degrees south of the equator. It takes measurements between 50 degrees north and 50 degrees south of the equator. The real-time processing and post-processing of the TRMM science data is performed by the TRMM Science Data and Information System (TSDIS). All TRMM products are archived and distributed to the public by the Goddard Distributed Active Archive Center (GES DISC DAAC).[6]

The (Level) 3B42 TRMM data product used in this paper is produced using the combined instrument rain calibration algorithm using an optimal combination of (Level) 2B-31 data (vertical hydrometeor profiles using PR radar and TMI data), (Level) 2A-12 data (vertical hydrometeor profiles at each pixel from TMI data), SSMI (Special Sensor Microwave/Imager), AMSR (Advanced Microwave Scanning Radiometer on board the Advanced Earth Observing Satellite-II (ADEOS-II)) and AMSU (Advanced Microwave Sounding Unit on NOAA geostationary satellites) precipitation estimates, to adjust IR estimates from geostationary IR observations. Near-global estimates are made by calibrating the IR brightness temperatures to the precipitation estimates. The 3B-42 data quantifies rainfall for $0.25^o \times 0.25^o$ degree grid boxes every 3 hours and the precipitation measurements range from 0.0 to 100mm/hr.

[5] http://podaac.jpl.nasa.gov/

[6] http://disc.sci.gsfc.nasa.gov/

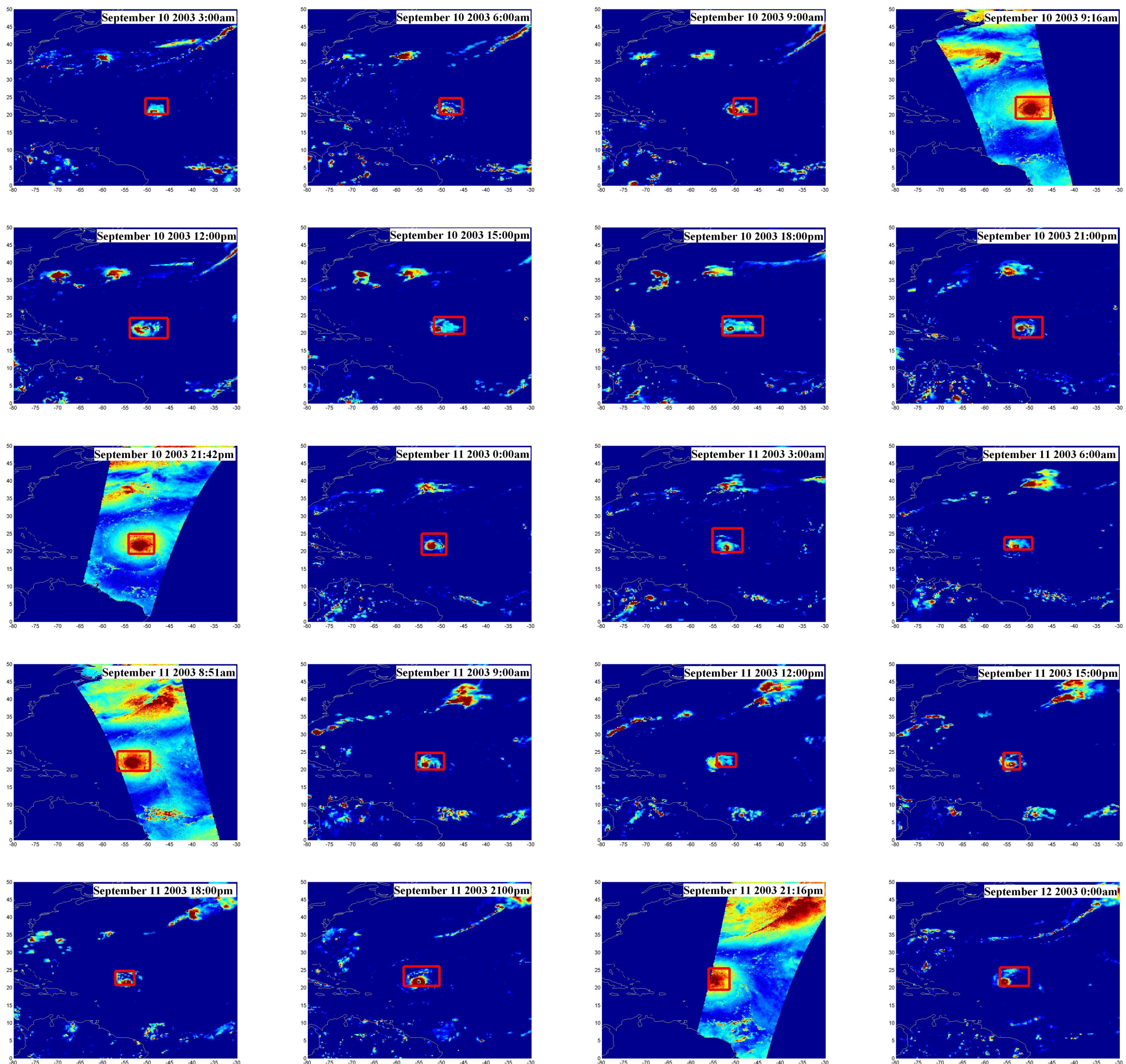

Figure 5: Two days tracking of Hurricane Isabel in 2003 using the QuikSCAT (gridded Level 2B swath data) and the TRMM (3B42 merged high quality/infrared precipitation) data. A red box bounds the detected cyclone.