Visualization Fusion: Hurricane Isabel Dataset

Ming Jiang* Naeem Shareef* Caixia Zhang* Roger Crawfis Raghu Machiraju Han-Wei Shen

The Ohio State University

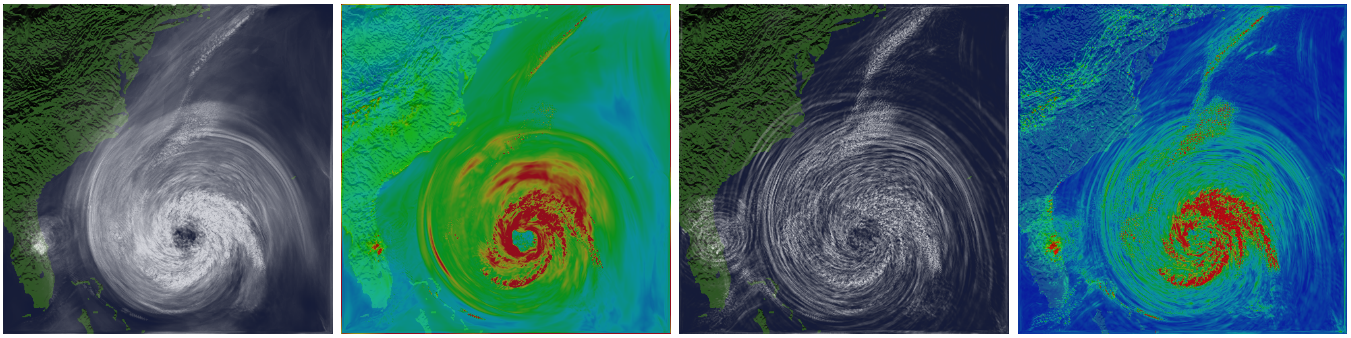

Figure 1: Volume rendering: emission only and maximum projection. (left) Vorticity magnitude. (right) Complex eigenvalues.

1 Introduction

Our main goal in developing visualization techniques for the Hurricane Isabel dataset is to engender better understanding of the underlying physical phenomenon. We want the visualization to produce novel insights into how a hurricane behaves across time, and how the various properties of the hurricane interact with each other. Most importantly, the visualization should tell us which parts of the hurricane are the most destructive, and when and where those destructive parts will reach Florida.

In this paper, we describe the various visualization techniques that we applied to the Hurricane Isabel dataset. Although we did not develop any new visualization techniques per se, we were able to effectively utilize existing ones in meaningful ways. Our primary contribution is adapting a set of existing algorithms and devising an overall framework for applying them to the dataset. In particular, we applied several vortex detection algorithms to the time varying dataset in order to automatically identify the various parts of the hurricane. We then developed a framework to automatically track the position of the hurricane across time, while computing both its translational velocity and maximum wind speed. Finally, we experimented with several volume rendering techniques to better understand some of the physical properties of the dataset.

2 Vortex Detection

A hurricane is a type of vortex [2]. It contains a central region, commonly referred to as the eye of the hurricane, surrounded by a multitude of swirling particles. What distinguishes a hurricane from other types of vortices is that the eye of the hurricane does not swirl. As we have shown in the images and movies, the wind speed near the eye of the hurricane is at a local minimum. As it turns out, this presents an interesting problem for most of the existing vortex detection algorithms.

We applied four popular vortex detection algorithms to the dataset. They are combinatorial method, normalized helicity, λ_2 method, and swirl parameter. A more detailed description of these algorithms can be found in [1]. Figure 2(top) show the results from applying two of the four vortex detection algorithms to time step 8 of the dataset. The results are colored as follows: combinatorial method (white), normalized helicity (magenta), λ_2 method (yellow), swirl parameter (cyan). The first thing to note is that none of the algorithms were able to detect the vortex core – the eye of the hurricane. Instead, what's detected are mostly shearing effects from the swirling particles surrounding the vortex core. What this means is that these detection algorithms are not very effective for this dataset. Furthermore, since all four algorithms utilize the velocity gradient tensor, it also means that other detection algorithms based on the velocity gradient tensor, such as the line-based methods, would be ineffective as well.

3 Hurricane Tracking

The purpose of experimenting with various vortex detection algorithms is to come up with ways to automatically identify the structures of a hurricane, starting with the eye. When working with time varying datasets, it is crucial to have a framework that can automate the identification process, which is an integral part of such analysis as tracking and predicting the path of the hurricane. Unfortunately, none of the detection algorithms was able to properly identify the central region of the hurricane.

To overcome this problem, we developed a framework to automatically identify the central region of the hurricane. It utilizes a technique that detects vortices as regions of low pressure. In order to automate this process for all time steps, we introduced a local minimum velocity magnitude criterion. Thus the eye of the hurricane lies within a region of low pressure with a local minimum velocity magnitude. Figure 2(bottom) shows the results from applying this framework to the dataset at time step 48. An isosurface is extracted for the low pressure; the surface is colored using

*Graduate student

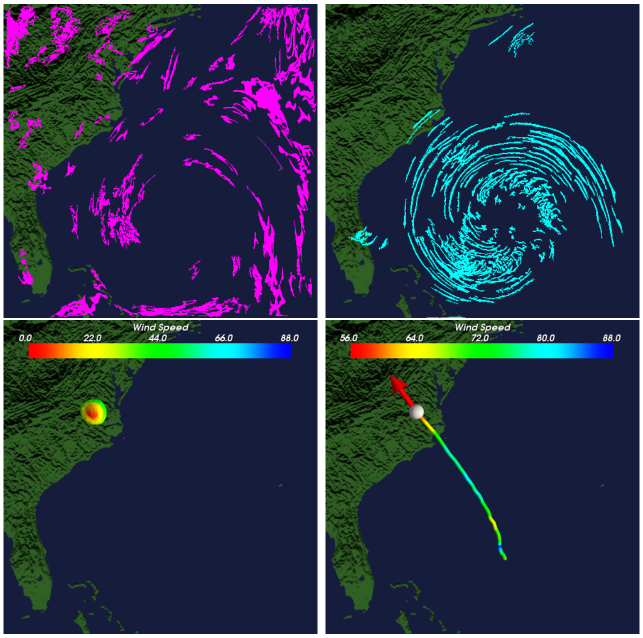

Figure 2: (top) Vortex detection algorithms: normalized helicity and swirl parameter. (bottom) Iconic visualization: hurricane tracking.

the velocity magnitude. What's unique about this framework is that it can correctly identify the central region of the hurricane without introducing any artifacts.

Figure 2(bottom) shows the results from performing hurricane tracking after automatically identifying the central region of the hurricane for all time steps. Iconic visualization is used to illustrate the path of the hurricane, the eye of the hurricane at each time step (the spheres), the translational velocity (the arrows), and the maximum wind speed (the colors). There are several interesting points to note from this visualization. First, when the wind speed is at its maximum, near time step 7, the translational speed of the hurricane is at its minimum – hurricane moves the slowest. Second, when hurricane is over land, near time step 48, its translational speed reaches its maximum – hurricane moves the fastest, while its wind speed decreases to its minimum. Lastly, one can use the translational velocity to predict how the hurricane will proceed on land for a short amount of time.

4 Volume Rendering

We use volume rendering as a tool to visualize and explore three key components used in most vortex detection algorithms: velocity magnitude, vorticity magnitude, and complex eigenvalues. The well known volume integration approach is able to show many values in the data simultaneously in a single rendering. Though, the visualization may become difficult to interpret if too much data is combined together with many colors to compute the final pixel color. We try to get around this problem by using alternatives to the well known absorption plus emission volume rendering method. Emission only rendering shows the accumulation of attribute values in the viewing direction to give overall structural information about the scalar field. Maximum Projection can show hot spots where maximum values occur.

The determination of informative transfer functions is a difficult problem in volume rendering and at the same time essential to provide insight into the data. We utilize a user-driven approach to search for transfer functions. This requires a system that can provide visual feedback at multiple frames per second every time the user changes the transfer function. We developed a tool that supports this task. It works by first pre-computing and storing view-dependent scalar information derived from the volume data. Then a viewpoint is chosen, called a view sample, to visualize the data from a particular vantage point. A camera and image plane are defined at the view sample and scalar information is collected and stored as texture data. An off-the-shelf PC graphics card is leveraged to quickly render the volume at interactive rates whenever the transfer function is changed, while the user's view is fixed at the view sample. Float textures are used to preserve the high precision found in the scalar data and the transfer functions.

We decided to use an emission only rendering model with no shading to compute the volume integration. We defined the transfer function to map scalars to grey level intensity values rather than to RGB colors so that we could clearly visualize the accumulation of the scalar field values at various locations. Our animations showing the velocity magnitude illustrates how well this rendering method was able to not only show gross structure, the extent of the hurricane, but also the rotational motion in time.

Maximum projection is able to show large values in the data, or hotspots. Here, color is very useful to clearly distinguish the intensity of the hotspot. We use the Maximum Opacity Projection, where the color associated with the maximum opacity along the viewing ray is assigned to the final pixel value. We constructed an RGBA transfer function with our user-driven approach. Our images and movies show a hot to cold color variation and a ramping opacity function emphasizing larger scalar values.

Figure 1 shows the results from applying the emission only and maximum projection to time step 8 of the dataset. Figure 1(left) shows the results for the vorticity magnitude. The hotspots correspond to regions where there are large amounts of local rotation – this can be useful for interpreting where the hurricane is likely to be most destructive. To reinforce this notion, we look to Figure 1(right), which shows the results for the complex eigenvalues of the velocity gradient tensor. The emission only image shows two sets of spirals: the larger one surrounding the hurricane eye, and the smaller one surrounding the hotspots arising on top of Florida.

5 Conclusion

The framework that we developed helps us to analyze the behavior of the hurricane as it evolves over time. We did this by automating the identification process in order to enable further analysis. One of the shortcomings of this approach is that it does not consider other variables such as cloud mixture or rain. Also, the low pressure–low speed method may not work for other types of swirling phenomena.

References

[1] M. Jiang, R. Machiraju, and D. S. Thompson. Detection and Visualization of Vortices. In *Visualization Handbook*. Academic Press, 2004.

[2] H. J. Lugt. *Vortex Flow in Nature and Technology.* Wiley, 1972.