

VISUALIZING UNCERTAINTY IN PREDICTED HURRICANE TRACKS

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While the error cone display produced by the National Hurricane Center is one of the primary tools used by officials, and the general public, to make emergency response decisions, the uncertainty underlying this display can be easily misunderstood. This paper explores the design of a display that provides a continually updated set of possible hurricane tracks, whose ensemble distribution closely matches the underlying statistics of a hurricane prediction. We explain the underlying algorithm and data structures, and demonstrate how our displays compare with the error cone. Finally, we review the design and results of a user study that we conducted as a preliminary test of the efficacy of our approach in communicating prediction uncertainty.

KEY WORDS: Hurricane prediction, Uncertainty visualization, Markov process, Kernel methods

1. INTRODUCTION

Although the past 30 years have seen major advances in the scientific understanding of hurricane forecasting, there has been a lack of systematic research on people's comprehension of the displays used to show these forecasts. Such work must be closely tied to data and predictions available from the National Hurricane Center [1]. The Center issues *advisories* every six hours during the life of a hurricane. An advisory provides the current position of the hurricane, the speed, current bearing, wind speed, and a prediction of the hurricane's position and intensity over the next five days. The positions are given in 12 hour increments for the first three days, and then in 24 hour increments over last two days. The Center also makes historical hurricane data, dating back to 1851, publicly available from its website. This dataset includes the latitude, longitude, speed, and bearing at six hour increments for the life of each historical track.

One of the primary visual aids provided by the National Hurricane Center is the *error cone*. An example of an error cone, also commonly referred to as the *cone of uncertainty*, is shown in Fig. 1. The center line represents the predicted hurricane track. The width of the cone is determined using historical forecast errors over a five year sample, and represents a 67% likelihood region for the actual hurricane track [2].

Some researchers have concluded that many people misinterpret the probabilistic concepts that are being communicated by the error cone [3]. The first problem is that the error cone tends to give the impression to those inside the cone that they have an exaggerated chance of being in the hurricane's path, while those outside of the cone tend to feel a false sense of security. In addition, it is very easy to misinterpret the cone as the region that will experience the effects of the hurricane, rather than as the region through which the hurricane path will likely pass.

To address these potential problems with the error cone visualization, we are investigating a new method that attempts to disaggregate the statistics of the error cone, in order to show the diversity and distribution of hurricane tracks that it might subsume. Our approach uses a display that is continuously being updated with candidate path

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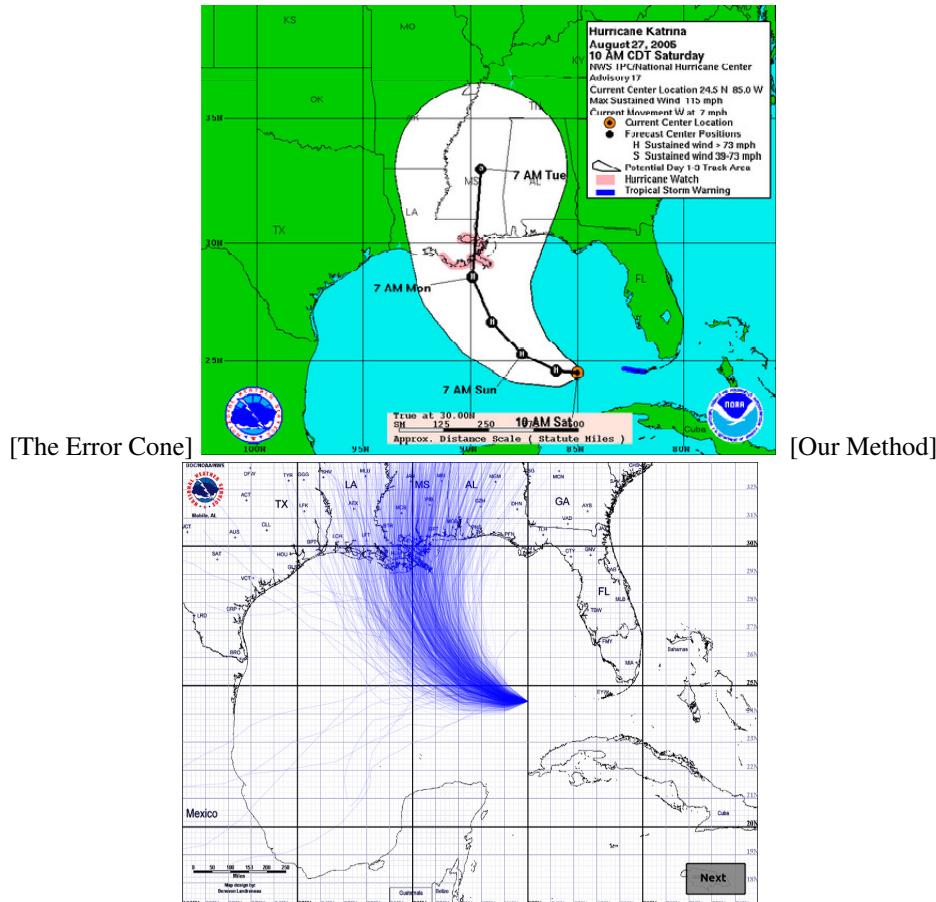


FIG. 1: Hurricane Prediction Visualization

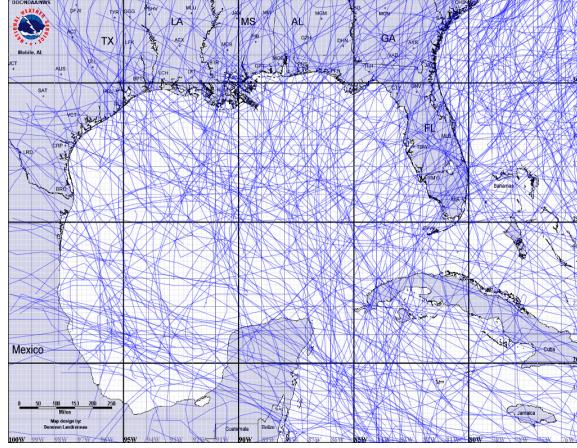


FIG. 2: Historical Hurricane Tracks Since 1945

predictions that are drawn from the distribution of likely paths represented by the error cone. We generate possible hurricane tracks, which are composited over each other, and fade out with time. Our assumption is that this type of display will be superior to the error cone in allowing subjects to more accurately predict the likelihood of a hurricane to affect a particular area, as indicated by their ability to describe the strike probability distribution indicated by the display.

The goal is to produce a display that shows a wide range of possible outcomes, while maintaining the statistical characteristics of the error cone. Simply generating these hurricane paths according to a Gaussian distribution about the predicted path would not be correct for two reasons. The first is the level of diversity. While hurricanes often track the predicted path, extreme deviations are not uncommon. Fig 2 shows all of the hurricane tracks in the Gulf of Mexico region since 1945. While some patterns can be seen in this historical data, the most salient characteristic is that the behavior of individual hurricanes can vary widely. The second is that we have no reason to assume that the area of prediction is normally distributed [NHC Reference]. In our work we use both the projected path of a hurricane as well as historical data to achieve a desirable level of path diversity.

2. BACKGROUND

2.1 Previous Studies

Clearly visualization tools that communicate information on the parameters and uncertainties of hurricane predictions need to be designed in formats that users are able to process quickly and effectively. While several visualization tools are available that describe the various parameters of a hurricane advisory, Broad et al. [3] have shown that the error cone is most widely used by officials and the general public as a means of evaluating the progress and prediction of a hurricane. Unfortunately, an evaluation of the available products during the 2004 Florida hurricane season showed that for many the error cone was not clearly communicating the probabilistic nature of the hurricane prediction or its potential path [4]. Not only was an inappropriate level of confidence assigned to the area within the cone, but in many cases the very nature of the cone and predicted track were misunderstood.

Despite its importance to officials and the general public, little has been done to test the interpretability or to develop alternatives that are likely to be better understood. There has some work on other issues related to hurricane prediction. For example, Steed et al. [5] presented an illustrated visualization method that displayed a hurricane's previous track and wind swath area by processing all of the advisories over the life of a hurricane. Martin et al. [6] presented a study that examined a user's ability to effectively judge the magnitude and direction of a hurricane's winds as a two dimensional vector field. While both showed interesting results, neither visualized the uncertainty associated with a hurricane prediction as a part of their method. We know of no other work developing alternative displays that

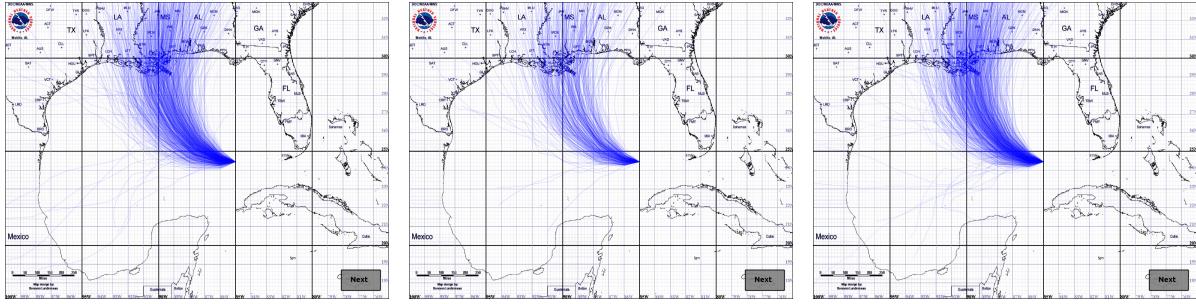


FIG. 3: Our Visualization at Three Different Times for the Same Advisory

attempts to show the natural uncertainty associated with hurricane predictions while still describing the most probable path.

2.2 Computing Distance and Direction on the Earth's Surface

All of the calculations used in our algorithm take into account the curvature of the Earth. These calculations are well known [7], but summarized here for convenience. To conform to the standards of navigation, a bearing of 0° is true north, and increases clockwise through 360° . Latitude is 0° at the equator, and 90° at the North Pole. Longitude is 0° at the Greenwich Meridian, increasing in the positive direction to the East. For the following formulas, (φ_i, ϑ_i) represent the latitudinal and longitudinal coordinates of a point i in degrees, and $R = 6371.0$ km is the radius of the Earth.

To determine the distance d between two points (φ_1, ϑ_1) , and (φ_2, ϑ_2) we use the Haversine formula,

$$\begin{aligned} a &= \sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos \varphi_1 \cos \varphi_2 \sin^2 \frac{\vartheta_2 - \vartheta_1}{2}, \\ d &= 2R \tan^{-1} \frac{\sqrt{a}}{\sqrt{1-a}}. \end{aligned}$$

The bearing from one point to another is given by

$$\theta = \tan^{-1}\left(\frac{\sin(\vartheta_2 - \vartheta_1) \cos \varphi_2}{\cos \varphi_1 \sin \varphi_2 - \sin \varphi_1 \cos \varphi_2 \cos(\vartheta_2 - \vartheta_1)}\right) + 180^\circ.$$

It should be noted that as a path is traveled from an initial position to a final position, the bearing will change continuously.

Given a starting position (φ_1, ϑ_1) , initial bearing θ , and distance d in km, the final position (φ_f, ϑ_f) is given by

$$\begin{aligned} \varphi_f &= \sin^{-1}\left(\sin \varphi_1 \cos \frac{d}{R}\right) + \cos \varphi_1 \sin \frac{d}{R} \cos \theta, \\ \vartheta_f &= \vartheta_1 + \tan^{-1}\left(\frac{\sin \theta \sin \frac{d}{R} \cos \varphi_1}{\cos \frac{d}{R} - \sin \varphi_1 \sin \varphi_f}\right). \end{aligned}$$

3. METHODOLOGY

Our method of depicting the uncertainty of a projected hurricane track uses a Monte Carlo process to repeatedly generate possible hurricane tracks. These tracks overlay one another and fade out over time, which gives the display a changing and dynamic quality as demonstrated in the three snapshots shown in Fig 3. Our algorithm uses a time varying probability density to generate tracks that closely follow the predicted path, and a Markov model, determined from historical data, to generate tracks that move away from the prediction. These are used to iteratively generate three hour sections of a track until the full track has been completed. Each of our generated tracks is initialized to the speed and bearing at the start of the current advisory. Once the initial speed and bearing is determined, a bearing and

speed change for the next section is generated from one of our probability models. This bearing and speed change is applied to the current speed and bearing to determine a new position.

As each path is initialized, the statistical properties of the paths already generated will help decide which of the two probability models will be used to determine the bearing and speed change for each segment of the new path. If 68% or more of the generated paths fit the error cone, then each segment of the path being generated has a 95% chance of using the Markov model to determine the speed and bearing change and a 5% chance of using the time varying probability density function. If less than 68% of the paths fit the error cone, then each segment of the path being generated has a 99% chance of using the time varying probability density function to determine the speed and bearing change, and a 1% chance of using the Markov model.

A generated path is said to fit the error cone if each point along the generated path is within a distance *d* of the corresponding point on the perimeter of the error cone at that point. *d* is determined by the width of the error cone at that point.

The rest of this section describes how the predicted path and historical data are each used to generate the speed and bearing changes that are applied to each path segment.

3.1 Using Predicted Data

In order to use the prediction from the current advisory for path generation, we treat the prediction as a time varying probability density function

$$p(\Delta\theta, \Delta s | t; \Delta t),$$

where $\Delta\theta$ is a random variable representing bearing change, Δs represents speed change, t is time since the beginning of the advisory, and Δt is a parameter for the time step over which change takes place. We discretize the time axis, yielding a set of fixed probability density functions of the form

$$p_t(\Delta\theta, \Delta s; \Delta t),$$

where t is the time at the start of a segment.

In order to build these time indexed density functions, we use the prediction data contained in the advisory. At each time step available in the prediction, we determine two corresponding points on the perimeter of the error cone. While the advisory provides location information for several points along the predicted path, the only initial information for the error cone is its width at specific points, which is determined by the National Hurricane Center on a yearly basis. Given a point on the predicted path, the corresponding points on the two sides of the error cone are uniquely determined by the width of the cone if we measure out this distance at a bearing of 90° from the predicted path. Linear interpolation is used on the predicted path and on the perimeter of the error cone to find sample points along each at three hour segments. The final bearing, initial bearing and speed at each of these points is then calculated. To find these values, we look at three consecutive points on a path segment, p_{i-1} , p_i , and p_{i+1} . The speed at point p_i is calculated by finding the distance from p_i and p_{i+1} and dividing by the number of hours in the segment (3 hours in our study). Fig 4 shows how the change in bearing $\Delta\theta$ is computed from these points. The final bearing θ_f for p_i is found by taking the bearing from p_i to p_{i-1} , and adding 180° . The initial bearing θ_i for p_i is the bearing from p_i to p_{i+1} . The bearing change at each point is just the minimal angular difference between the final bearing and initial bearing. The speed change is the speed difference between p_i and p_{i-1} . These speed and bearing changes are then used to make a probability density function for the bearing change and for the speed change at each of the three hour marks of our advisory.

We approximate the probability density function governing bearing change at each time step by estimating the probabilities of a small set of bearing changes, and interpolating between them. In our work we are using 101 samples. The central sample value c is set to the bearing change of the corresponding point on the predicted path. The minimum and maximum bearing changes sampled are

$$\begin{aligned} m &= c + 1.5(\min(\Delta\theta_l, \Delta\theta_r) - c), \\ M &= c + 1.5(\max(\Delta\theta_l, \Delta\theta_r) - c), \end{aligned} \tag{1}$$

where $\Delta\theta_l$ and $\Delta\theta_r$ are the bearing changes on the left and right sides of the error cone at the current time. Half of the remaining samples are evenly spaced from m to c with the other half evenly spaced from c to M . Equation

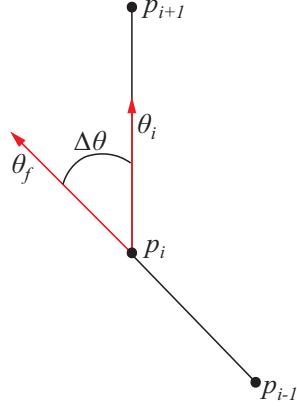


FIG. 4: Initial Bearing and Final Bearing

1 provides a support that is 1.5 times the distance between the minimum and the maximum bearing changes, giving support outside the error cone. Note that the distance between the samples on the lower half of the distribution will generally not be the same as the distance between the samples on the upper half.

The probabilities corresponding to each sample are estimated as

$$p(\Delta\theta) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\Delta\theta - c)^2}{2\sigma^2}},$$

where $\Delta\theta$ is the sample value, the standard deviation σ is set to $c - m/3$ if the sample bearing change is less than c or set to $M - c/3$ if it is greater than c . This gives a distribution on each side of the predicted path that reaches two standard deviations at the error cone edges. Once the probabilities of each of the samples have all been found, the set of samples is scaled so that the total area under the curve, estimated using the trapezoidal rule, is 1.0. Fig 5 shows an example distribution shape, which will typically not be Gaussian. Speed changes are processed in exactly the same manner.

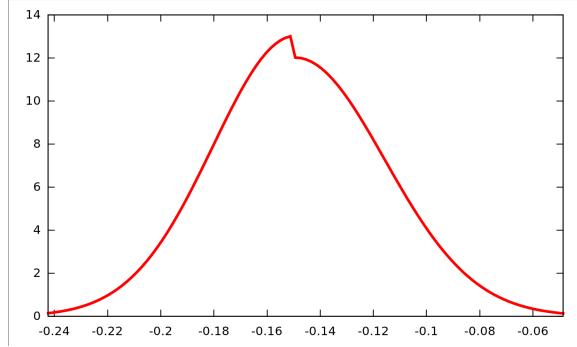
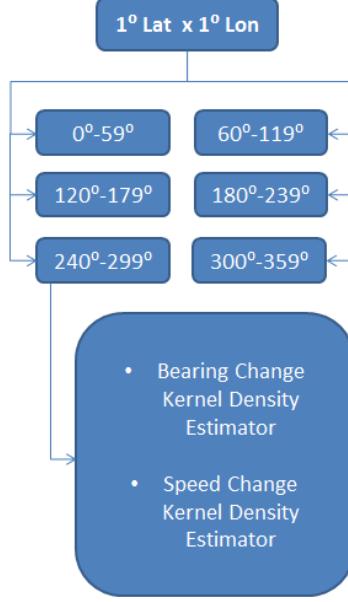


FIG. 5: Time Varying Probability Density Function Using Predicted Path Data

When using the predicted data to generate the bearing and speed change for a given segment, the appropriate probability density function is indexed by the current time. We generate a random number from 0 to 1, numerically integrate the probability density function using the trapezoidal rule until the integration reaches this number, and return the corresponding bearing.

Speed change is determined similarly, with the exception being the computation of m and M . To include speed changes that allow for the generated hurricane tracks to reach the full range of area inside the error cone, these

**FIG. 6:** Historical Datastructure Grid Cell

equations have been modified to

$$\begin{aligned} m &= c + 3.0(\min(\Delta\theta_l, \Delta\theta_r) - c), \\ M &= c + 3.0(\max(\Delta\theta_l, \Delta\theta_r) - c), \end{aligned} \quad (2)$$

The use of the probability density function allows us to generate speed and bearing changes that tend to create paths falling within the error cone, with highest density near the center of the cone.

3.2 Using Historical Data

Unlike our treatment of the predicted data, we represent the history of hurricane paths with a Markov model, which we use to determine bearing and speed changes given a hurricane's current location, speed and bearing. If the bearing change random variable is $\Delta\theta$ and the speed change random variable is Δs , such a model would be summarized by the conditional probability density function

$$p(\Delta\theta, \Delta s | \theta, s, \varphi, \vartheta; \Delta t),$$

where θ is the current bearing, s is the current speed, φ is the current latitude, ϑ is the current longitude, and Δt is a time-step parameter.

In our current method, we make the assumption that change in direction and speed are independent of the hurricane's current speed, reducing the conditional probability to

$$p(\Delta\theta, \Delta s | \theta, \varphi, \vartheta; \Delta t).$$

This means that when we consider historical hurricane tracks in building our model, we need only concern ourselves with the position of the hurricane and its current bearing. In this way we attempt to preserve spatially local patterns found in past hurricane activity.

This conditional probability specifies two continuous three dimensional functions, which we discretize, first by sampling over spatial grid cells, each representing one degree of latitude and one degree of longitude, and then by

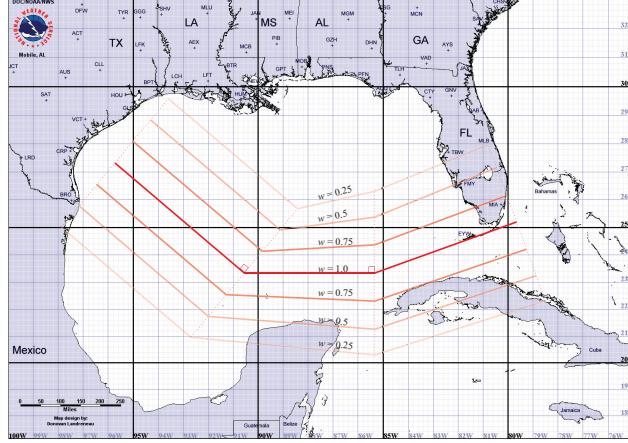


FIG. 7: Propagation of a Historical Path

bearing, assigning a set of six bins to each grid cell, each covering 60° . We capture this discretization by constructing a two dimensional data structure over the Gulf coast of the United States, where the cells can be represented as a rectangular grid on a Mercator Projection map. Thus, the probability density functions at cell (i, j) , for hurricane paths with bearing in the angular range k are given by

$$p_{ijk}(\Delta\theta, \Delta s; \Delta t).$$

We estimate these functions for each angular bin, by noting the bearing and speed of each historical path as it enters the grid cell, the time it spends in the cell, and its bearing and speed when it leaves the cell. Each entrance and exit constitutes one sample, which we use to construct kernel density estimators for the bearing and speed changes. The resulting data structure has entries of the form shown in Fig 6.

Although historical hurricane track data is available back to 1851, in our work we use only data starting from 1945 due to concerns relating to the validity of earlier measurements. Because this data is generally too sparse to provide adequate samples for our kernel density estimators, we generate three supplemental parallel paths on each side of every historical path, as shown in Fig. 7. The parallel paths are created by stepping along each point of a historical path while generating three corresponding points at 60 km intervals in both directions perpendicular to the historical path. To assure that actual historical paths have a greater contribution to the probability density function than the parallel tracks, every path is assigned a weight value w , with original historical paths having weight 1.0 and the parallel paths having weights 0.75, 0.5, and 0.25.

All of the historical and supplemental paths are intersected with the spatial grid cells, and used to construct two kernel density estimators for every bin in each grid cell. These approximate the two required probability density functions governing bearing change and speed change. Because the point at which a hurricane enters and leaves a grid cell, as well as its bearing and speed at these respective points, is not directly available to us through the historical records, we determine them using linear interpolation.

To build the probability density function for the bearing change, we must determine the supports of the kernel density estimator in each bin. To do this, we determine the mean and standard deviation over all of the bearing changes stored in a bin, and then extend the minimum and maximum by three standard deviations.

The value of the kernel density estimator, K , for bearing change $\Delta\theta$ for a single bin in a grid cell is computed as a weighted sum of Gaussian kernels centered over each of the bearing change samples. Assuming n samples in the bin, and letting w_i be the weight and c_i be the bearing change of sample i , we have

$$K(\Delta\theta) = \frac{1}{W} \left(\sum_{i=0}^n \frac{w_i}{\sigma\sqrt{2\pi}} e^{-\frac{(\Delta\theta - c_i)^2}{2\sigma^2}} \right) \quad (3)$$

where $W = \sum_{i=0}^n w_i$, and σ is the standard deviation of all the bearing change samples in a bin.

Equation 3 gives the function needed to compute the bearing change. However, it is not efficient to compute this every time it is needed, so we discretize and later interpolate when we need a value. In our algorithm, we use 11 samples evenly spaced across the supports. To account for discretization error, the curve is finally scaled so that the area under the curve, computed using the trapezoidal rule, is 1.0. The probability density function for speed changes is computed in the same manner. An example of a resulting density function is shown in Fig 8. The horizontal axis represents bearing change. The green curves show individual samples inside the summation of equation 3. The area under a green curve indicates its weight. The red curve displays the final interpolated kernel density estimator.

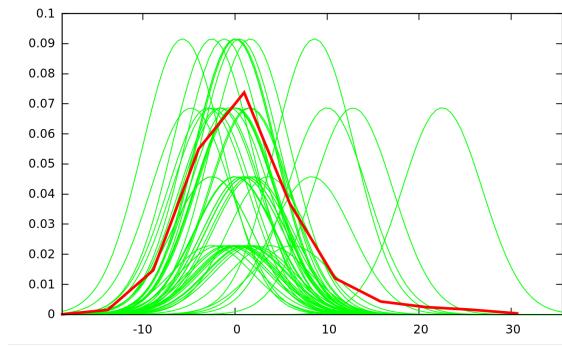


FIG. 8: Example Kernel Density Estimator Construction

When it is determined that historical data should be used to predict the bearing and speed change for a given segment, the appropriate bin is determined from the generated path’s current location and bearing. The latitude and longitude indicate the grid cell while the bearing indicates the bin. The bearing and speed probability density functions from that bin are then used to generate a speed and bearing change that is consistent with the historical data.

4. STUDY

We have run an experiment which aims to test for any differences in how users estimate the hurricane strike probability distribution when using our visualization method compared to using the error cone. Our hypothesis is that with our method, they will show a broader distribution of probabilities, which more closely reflects the uncertainty inherent in a hurricane advisory. To test this, a sequence of six historical advisories will be displayed to participants. Each advisory will be shown twice consecutively, once with the error cone and once with our visualization method. The order that the methods were shown was alternated between participants so that half saw the error cone first and half saw our visualization method first. The order of the historical advisories was the same for all participants.

As shown in Fig. 9, a map of the Gulf of Mexico region was displayed, with a circle divided into eight sectors centered over the current position of the hurricane. The sides of the sectors were aligned to the cardinal directions. Users were asked to place a set of numbered chips on the circle to indicate their estimate of the probability that the hurricane will exit the circle in this sector. Thus, we are able to gauge each participant’s ability to estimate probability by measuring the distribution of these chips across all of the sectors.

The chips have values ranging from 1 to 20, with the cumulative value of all the chips being 100. The interface assures that each chip is assigned to exactly one sector. To advance from one advisory to another, all of the chips must be assigned.

5. RESULTS

Based on a statistical analysis of the data resulting from the user study, we were unable to conclusively determine whether our method increased an individual’s understanding of the uncertainty associated with a predicted hurricane

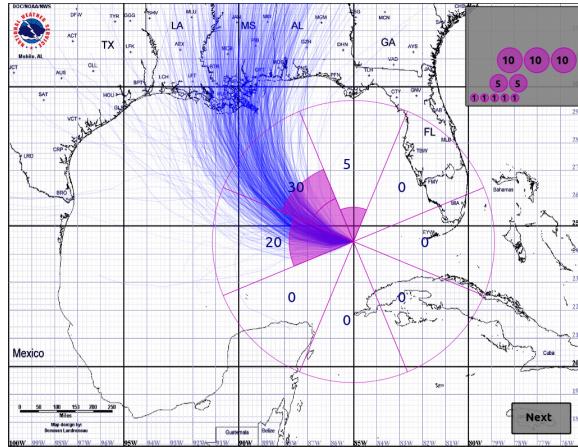


FIG. 9: Interface for Our Experimental Design

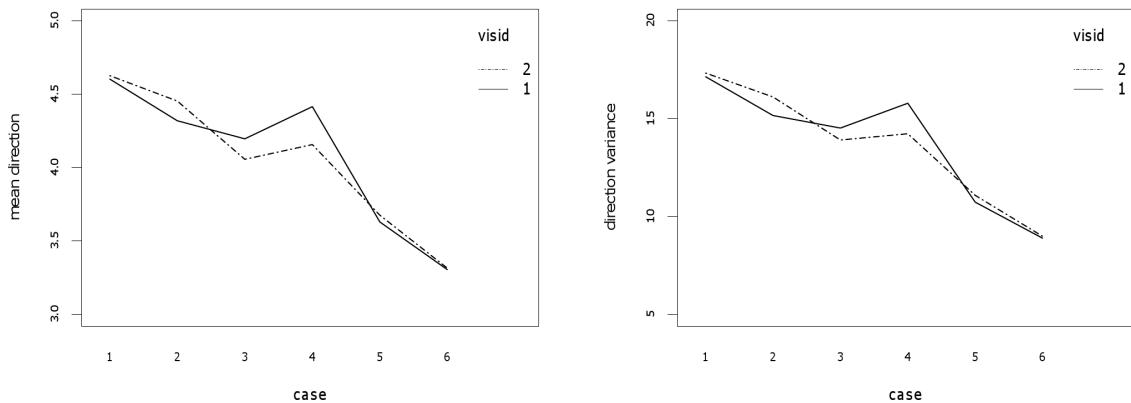


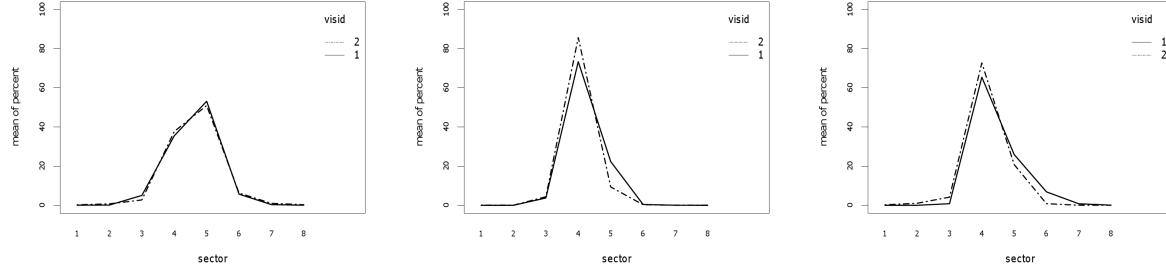
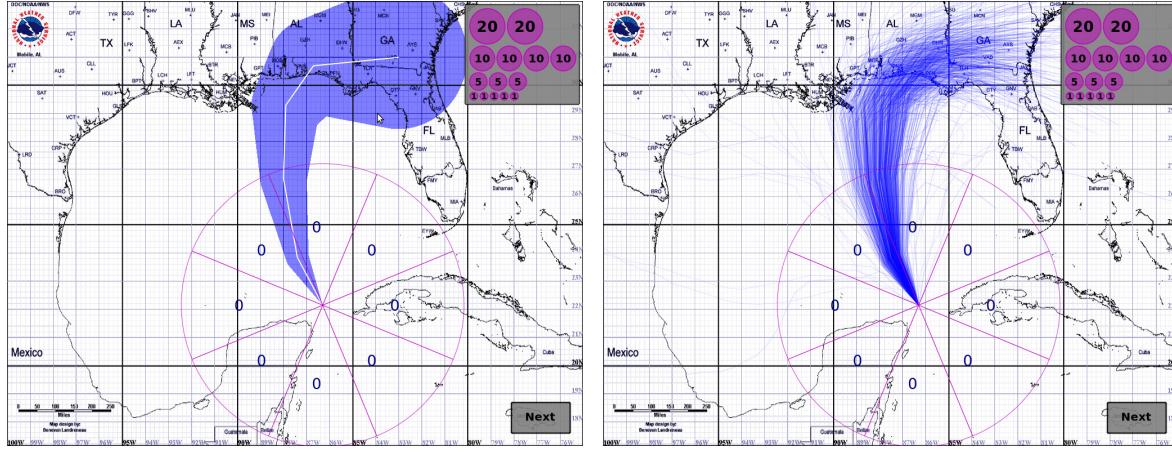
FIG. 10: Direction Mean and Variance

track compared to that of the error cone. To come to this conclusion, we first looked at the directional mean and variance across all of the hurricane cases. This is illustrated in Fig. 10. In these figures, the *visid* indicates the method used with 1 representing our visualization tool, and 2 representing the error cone. The mean direction indicates the sector central to the distribution of the percentage points. The variance describes the variance of the percentage point distribution across the sectors.

For all of the graphs shown, sector 1 corresponds to the sector facing directly south. The sectors continue clockwise, with sector 7 pointing to the south east. From Fig. 10, we can tell that hurricane cases three and four have a statistically significant difference in how the percentage points were distributed across the sectors between the two visualization methods. For the remainder of the cases, there was no statistically significant difference.

A closer look at hurricane case one shows that the distribution of percentage points for both our visualization tool and the error cone was almost identical for all sectors, as can be seen in Fig. 11. When we do the same comparison for hurricane cases three and four, we can see that the participants gave a broader distribution of percentage points to the sectors, adding a few percentage points to the north and north east sectors.

In these figures, the y axis shows the mean percentage assigned to each sector, while the sectors are labeled across

**FIG. 11:** Analysis of Three Hurricane Cases**FIG. 12:** Hurricane Case 1

the x axis. Further inspection into these different cases revealed an interesting observation. In case three the error cone was entirely in a single sector. In case four, only a small portion of the error cone was in a second sector, and this area did not approach the outer perimeter of the sector. For the rest of the cases, the area of the error cone was more evenly split between two adjacent sectors. This leads us to speculate that an additional study with a more fine grained analysis may be needed to determine the overall significance of the difference between the two visualization methods.

The qualitative analysis was much more deterministic. We asked our participants to rate which visualization method they preferred on a scale of 1 to 5, with a 1 indicating that they strongly preferred our method, and a 5 indicating that they strongly preferred the error cone. Of the 23 participants, only one person indicated that they slightly preferred the error cone, with a score 4. All other responses were either a strong preference for our method with a score of 1, or slight preference, with a score of 2. The mean score over all of the participants was 1.56, and the variance was 0.5296.

One consistent criticism of our method was that while it was more visually interesting to watch, it was also more difficult to look at than the error cone. However, the participant's feedback also suggests that our method gave the users a better overall understanding of the uncertainty and unpredictability associated with forecasted hurricane tracks.

6. CONCLUSION

We have presented a visualization method as an alternative to the error cone display produced by the National Hurricane Center. Our method presents an ensemble of continuously updated tracks demonstrating the range of possible

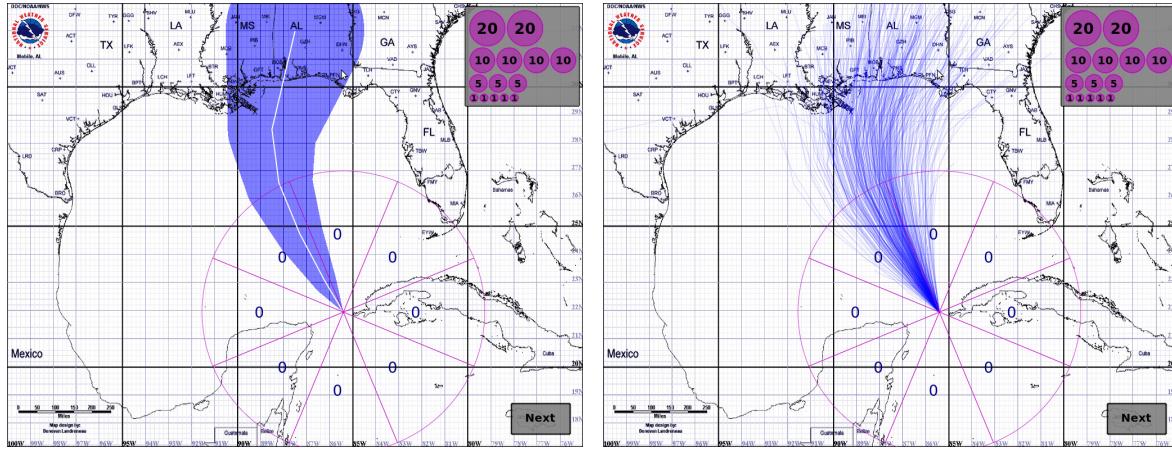


FIG. 13: Hurricane Case 2

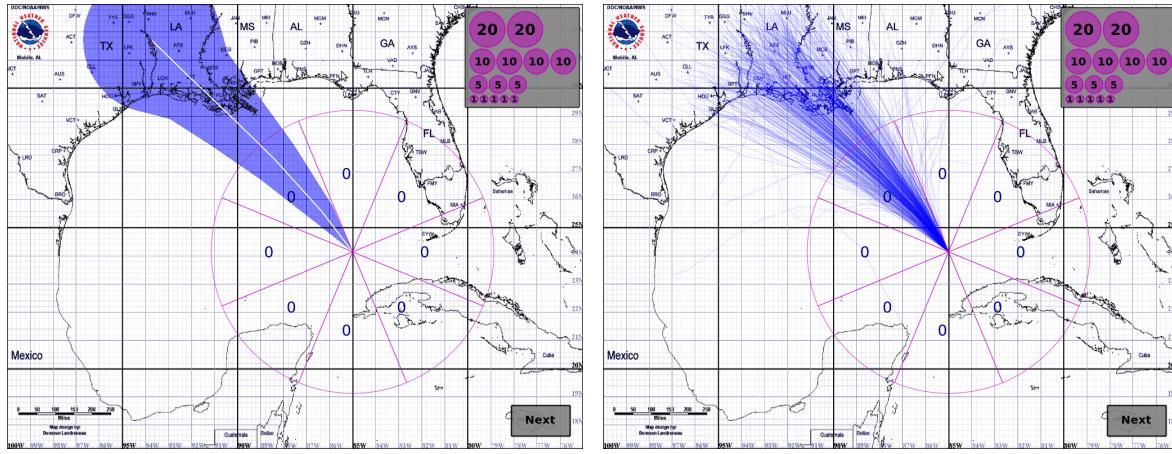


FIG. 14: Hurricane Case 3

hurricane outcomes. It uses both a hurricane's current advisory information and data on historical hurricanes to create a dynamic display showing the variety of possible hurricane tracks. This approach produces tracks that lie both inside and outside the error cone, while maintaining statistical characteristics similar to those underlying the hurricane advisory.

One problem that we have encountered with our method is its reliance on the current speed and bearing of a hurricane to generate tracks. In the event that the hurricane is listed as stationary, or if the current speed and bearing differ widely from the speed and bearing required to get to the next position listed in the advisory, the statistical properties of our tracks sometimes diverge from those of the error cone. In these situations, the paths can become much too widely and evenly distributed. This problem is currently under study.

Future work will include refining the algorithm, running additional user studies to investigate the how users perceive the uncertainty of a predicted hurricane track related to areas within the error cone and for particular geographical locations, and using our method as a base to support other visualization tools. One idea is to generate a heat map from the generated tracks, and use it to create a three dimensional display that describes the probability of a hurricane track in terms of a height field. This could be displayed in a 3D view, or a section through this view, following the coastline, could be displayed in 2D. Another possible visualization would be to superimpose our method over the

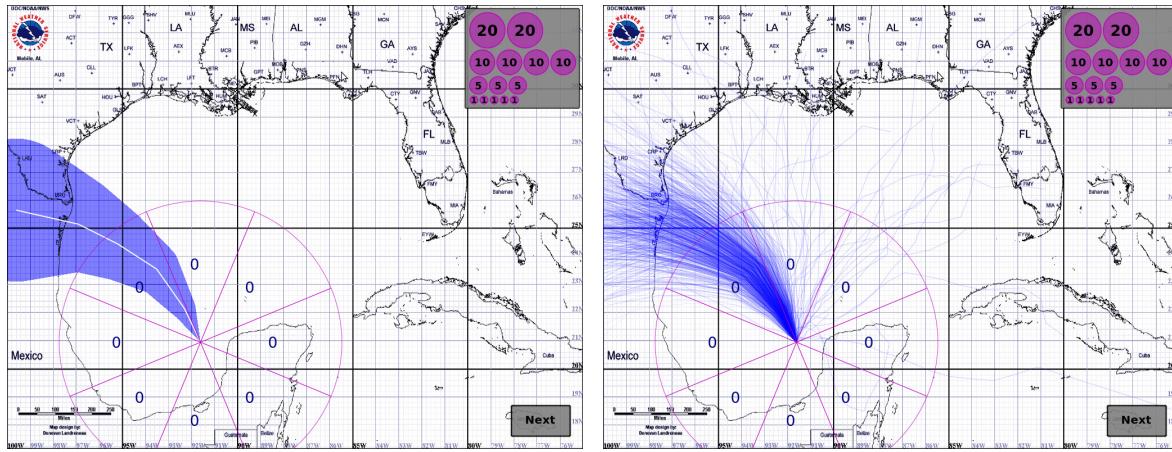


FIG. 15: Hurricane Case 4

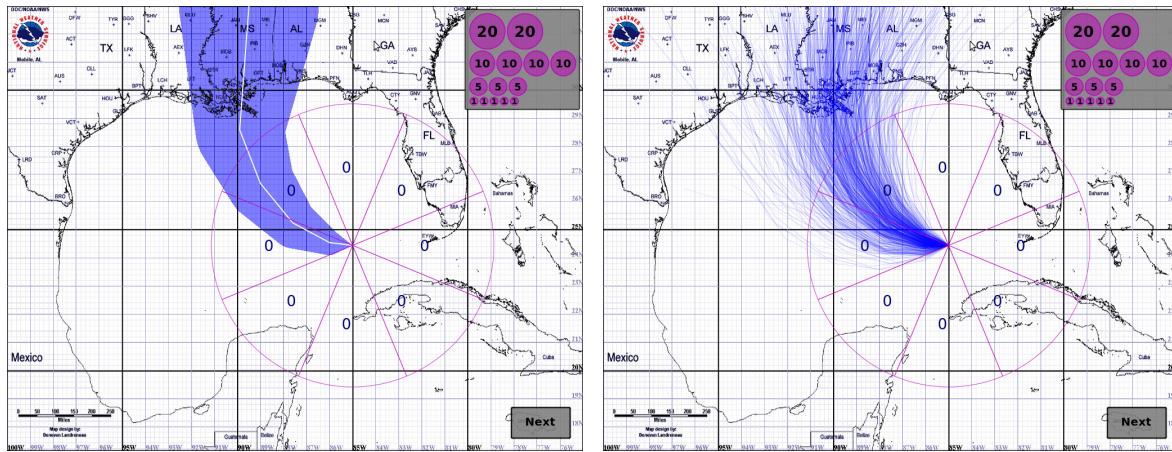


FIG. 16: Hurricane Case 5

error cone, so that both summary statistics and detailed outcomes can be viewed. We would like to explore methods to incorporate other important hurricane information, such as wind speed and storm shape, into the display. Finally, it would be useful to design a tool to assist in evacuation decision making, which would require integrating evacuation and hurricane models.

ACKNOWLEDGMENTS

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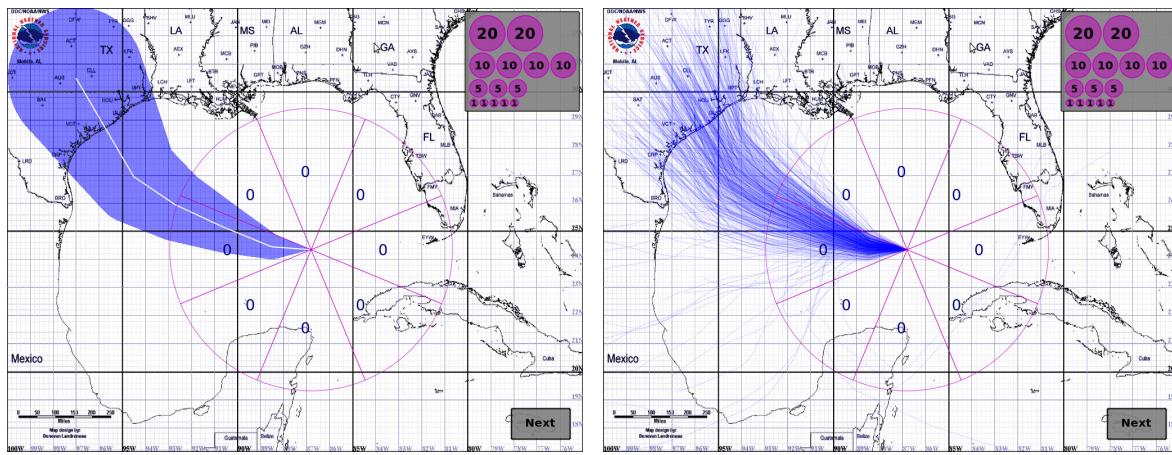


FIG. 17: Hurricane Case 6

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