ADAPTIVE, MODEL-DRIVEN OBSERVATION FOR EARTH SCIENCE

Virtual Conference 19–23 October 2020

P. Tavallali[1], S. Chien[1], L. Mandrake[1], Y. Marchetti[1], H. Su[1], L. Wu[1], B. Smith[1], A. Branch[1], J. Mason[1], J. Swope[1]

[1]Jet Propulsion Laboratory, California Institute of Technology,
4800 Oak Grove Drive Pasadena, CA 91109, firstname.lastname@jpl.nasa.gov

ABSTRACT

In this article we introduce a preliminary effort to apply an adaptive and model-driven sensing framework to the study of large scale storms. Such systems pose great challenges as studying complex, fast developing Earth science phenomena such as hurricanes have significant spatial extent and complex temporal evolution making comprehensive sensing of the entire phenomena prohibitive. We use adaptive sensing to direct sensing in an autonomous and intelligent cycle. We show how online analysis would increase the knowledge of the event and decrease uncertainty in predictions.

1 INTRODUCTION

Studying complex, fast developing Earth science phenomena such as hurricanes and other extreme weather events is a tremendous challenge. Such phenomena have significant spatial extent and complex temporal evolution, making comprehensive sensing of the entire phenomena prohibitive.

Adaptive sensing is a technique in which dynamic analysis of the phenomena is used to direct sensing in a virtuous cycle. Online analysis is first used to determine sensing actions that are most likely to increase knowledge of the event, then sensing is directed to the area/modality, consequently new data is acquired, and it is finally assimilated into the model. This cycle is repeated to address the spatiotemporal dynamics of the studies system.

We describe an initial effort to apply adaptive sensing to the study of large scale storms such as hurricanes and typhoons. In this effort, we conduct simulations of a storm. We then use these simulations to drive analysis to estimate the impact of a range of sensing actions on improvement of the model forecast ability, characterizing this as an estimation of a sensing utility function. A sensing planner then develops a sensing plan using this utility information, attempting to maximize utility gain that is subject to operational constraints of the sensor platforms (marine, aerial, space, etc.). These observations are acquired and the cycle continues.

The core principle of this approach is that deliberative direction of sensor assets will be more effective than current undirected or ad hoc strategies for sensing. This approach, therefore, results in improved model accuracy and consequently science. This approach is shown below in Figure 1.

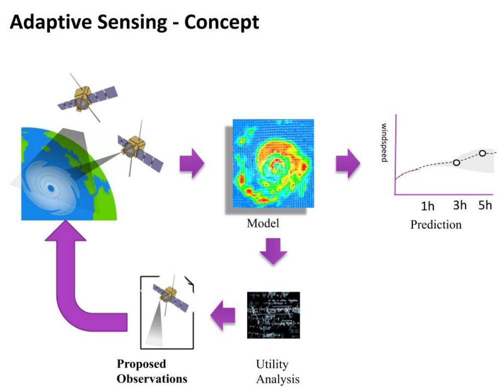

Figure 1: Adaptive Sensing Concept.

2 HURRICANE MODELING

Numerical Weather Prediction Models (NWP) generally perform well in predicting the large-scale dynamic and thermodynamic environments of hurricanes and thus hurricane tracks. However, they have difficulties in predicting hurricane intensity change, especially rapid intensification (RI) defined as storm maximum sustained wind speed increase more than 30 knots (35 mph) in 24 hours [5]. Previous studies showed that assimilating satellite or in-situ data can significantly improve hurricane intensity forecast [5,15]. The forecast improvements can be measured by reduced bias in ensemble forecast mean relative to the truth and/or reduced ensemble spread across the ensemble members. In this paper, we describe the hurricane modeling and utility estimate framework using a 60-member ensemble simulation of Hurricane Harvey (2017) generated by the Weather Research Forecast Model with Ensemble Kalman Filter (WRF-EnKF) system developed at the Pennsylvania State University (PSU) [4].

Hurricane Harvey (2017) was one of the costliest tropical cyclones on record with more than $100 billion economic loss. It was a Category 4 hurricane that made landfall on Texas and Louisiana in August 2017, causing catastrophic flooding and many deaths. It underwent RI before the landfall; but none of the operational NWP models correctly predicted its RI. We examine here what observations could potentially improve the model forecast of Harvey's sudden intensity change during August 24-26, 2017.

We use 3 nested domains with horizontal resolution of 27, 9 and 3 km in the PSU WRF-EnKF model. The outermost domain has fixed boundaries but two inner domains center on the eye of the storm moving northwestward. The three domains at the initial time of 12Z August 24, 2017 are shown in Figure 2.

Figure 2: Three nested model domains for the simulations of Hurricane Harvey (2017) at the initial time of 12Z August 24, 2017.

48-hour forecasts are conducted with 60 different initial conditions created by adding random perturbations to the initial temperature and moisture fields. Model-simulated 3-D temperature, moisture, and wind profiles are saved every hour, along with rain rate, cloud mass, and surface pressure. The evolution of Harvey's minimum sea level pressure (MSLP) as a measure of storm intensity from the 60 ensemble members are shown in Figure 3. The observed MSLP from the NHC Best-Track analysis is shown in black (Figure 3). These simulations used initial conditions generated from the WRF-EnKF simulations that assimilated GOES-16 all-sky radiances (not used in operational NWP models). This assimilation captures Harvey's RI processes in two days after the initiation. However, there is a large spread in the simulated storm intensity among the ensemble members, and large biases exist relative to the observation. Our utility estimate targets how much of ensemble spread in MSLP can be reduced by ingesting certain measurements at certain locations.

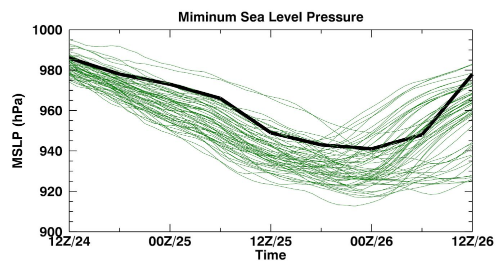

Figure 3: Ensemble forecasts (green) of Hurricane Harvey's minimum sea level pressure. The NHC best-track (black) is also shown.

3 UTILITY ESTIMATION

3.1 Utility estimation

Hurricane forecast models can be used to directly compute the impact of local measurements on the model output [1]. At the same time, their computational costs are prohibitive. Hence, one solution would be to estimate the utility of the proposed planned observations. This can be done through approximating ensemble-based forecast sensitivity [6] with efficient statistical and machine learning models. Ensemble-based forecast sensitivity is one of the metrics that is currently employed for measuring the impact of targeted observations of convective systems on their forecasts [7,8,9]. In effect, this metric is estimating the potential reduction in the forecast uncertainty [8]. In other words, it is a measure of the quality of a hurricane prediction [10,11]. Technically, forecast sensitivity accounts for the covariance of a measured variable and a forecasted variable, and is essentially a linear model of these two variables. Importantly, it does not require the knowledge of the "true" value of the forecasted variable since it approximates reduction in uncertainty rather than a forecast error. Forecast sensitivity can be computed for individual spatial locations and variable of interest independently.

Hence, ensemble-based forecast sensitivity can be used as a proxy of a utility function for the planning system. Figure 4 shows an example of a preliminary utility estimate computed using a linear univariate sensitivity between local measurements of temperature at 3.5km (Figure 5, left) and MSLP (Figure 5, right) as a forecast metric from the Hurricane Harvey study. The utility estimation expressed in Figure 4 indicates that the red areas of the map are of higher utility and would reduce the uncertainty of the minimum sea level pressure forecast to a greater extent compared to the blue areas.

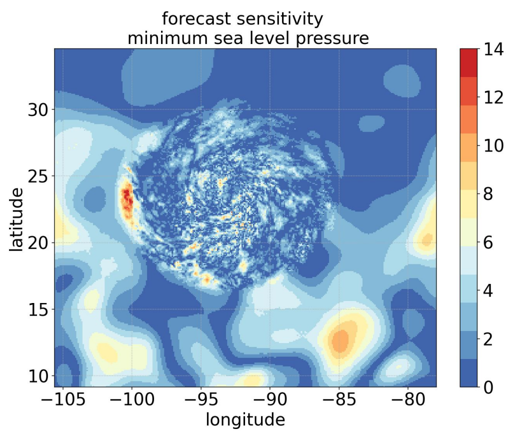

Figure 4: Example of a proxy measurement utility function. The utility corresponds to the d02 area in Figure 2. The utility function is computed for a 12-hour forecast window.

The estimation of the forecast sensitivity, however, relies on the availability of the forecast, which can take considerable computation time. Therefore a natural extension to this approach is to use a machine learning model of the forecast sensitivity that is pre-trained over the data. The Harvey hurricane study, described above, provides observational, assimilated and forecast data that can be used directly to build and validate such a machine learning utility model. For example, the preliminary model input variables would include temperature, water vapor and brightness temperature. Hence, in this machine learning context, the utility can then be predicted directly via a trained machine learning model for a given initial observed state, e.g. brightness temperature, at the beginning of each targeted observation campaign. Once the observations are collected by a sensing system, the utility is then re-estimated.

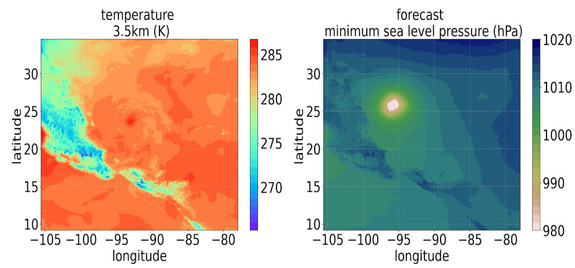

Figure 5: Temperature at 3.5km (left) and minimum seal level pressure forecast (right) used in computing the utility.

3.2 Validation and data denial

The validation of the ensemble-based sensitivities and the utility model must be conducted through data denial experiments. In such experiments, we will first run a high resolution forward model of a hurricane, then estimate the utility of observations for certain forecast intervals, and then finally compare the reduction of error when the observations are collected versus when they are not. In essence, this approach validates the effectiveness of the forecast sensitivity suggested observations with a baseline that no data is collected or collected at random.

4 SENSOR PLANNING

In the prototype under implementation, the planner (resource allocator) then allocates measurements, with the objective of optimizing measurements according to the provided utility function. We are currently examining sensor allocation strategies for both space assets (Geostationary with pointing capability within a fixed field of regard and Low Earth Orbit with a field of regard related to a fixed overflight path) as well as Aerial and In-situ assets with deployment, path planning, and possibly recovery constraints.

4.1 Planning for Orbital Assets

Problem Definition: The objective for the orbital assets problem is to formulate an observation schedule for a satellite to maximize the utility function. The planner is provided with a maximum time horizon, a utility map, and a slew model. We currently focus on a geostationary satellite scenario, using GOES-16 as a model. We chose GOES-16 due to the relevance of the Advanced Baseline Imager's (ABI) mesoscale mode. We define each image as covering one pixel of the utility map. We slew between all subsequent observations calculating the time as a function of slew angle and a fixed slew rate. While this slew model is unrealistic, it could be updated without affecting the observation problem. The utility function is the sum of all individual utilities for each unique observed pixel.

Planning Approach: The objective for the satellite problem is an observation plan of targets that maximizes utility while minimizing the slew cost, given a time constraint. We decompose the problem into two separate problems: (1) selecting the best targets and (2) optimizing the slew path between targets. This decomposition will facilitate extension to a non-modular utility function.

To select the best targets we search for the optimal number of targets n. We first pick the n targets with the largest utility, and then solve the slew path problem with those targets. We then iteratively increase or decrease this n based on the remaining observation time.

The shortest slew path problem is equivalent to the Travelling Salesperson Problem (TSP) where the targets are the nodes and the slew times between targets are the edges. We use Google's OR-Tools [12] to find an approximate solution to the problem. An initial greedy solution is found then iteratively improved using Guided Local Search (GLS). To allow starting and ending at any target, we start at a dummy node that has zero cost transitions to every other node.

In Figure 6 we show the resultant path derived by the Geostationary observation scheduling algorithm. The utility map is relevant for a timeframe of 6 hours. ABI can take 2 mesoscale images a minute, which is 720 observations over 6 hours.

Figure 6: Satellite observation plans to maximize the utility of measurements. The utility map is for a timeframe of 6 hours. The plot shows a plan with 720 observations, or 1 image every 30 seconds, which is the maximum images that ABI could take. The observations are red circles and the slews are light red lines.

4.2 Planning for Aerial Drones

Problem Definition: The objective for the aerial drones problem is to plan a set of paths of a given length for multiple vehicles to maximize the collected utility. The planner is provided with the drones starting locations, the maximum time horizon, and the utility map as inputs. The search space is discretized into 2D cells with dimensions equal and co-located with the utility map seen in Figure 4. Time is discretized such that it takes one timestep to move between cells. The drones are only allowed to transition from a cell to one of the 4 orthogonal cells. The utility function is the sum of all individual utilities for each unique visited cell. If a cell is visited twice, it only contributes utility once. This problem is similar to the Multi-robot Informative Path Planning (MIPP) problem presented in [16] and the Travelling Salesman Problem with Profits (TSPP) [17].

Planning Approach: The problem outlined can be shown to be NP-Hard based on a reduction from the Hamiltonian Path Problem (HPP) on grid graphs [13]. This is done by setting all cells that correspond to a node in the grid graph to utility 1 and all other cells to utility 0. Then at each possible starting location find the path of N nodes with maximum utility. If any path has a utility of N then that is a hamiltonian path, otherwise there is no hamiltonian path in the grid graph. Therefore an optimal solution is not expected for large problem sizes. Our approach uses a structure and process similar to that of Dynamic Programming (DP). However, with a non-optimal substructure. We find in practice that although the solution is not optimal, it is of acceptable quality.

Our approach is as follows. Create a 3-D array U of size (X,Y,T) where X and Y are the sizes of the utility map and T is the number of timesteps for the time horizon of the path. Initialize $U[s_x,s_y,0]$ to 0 where s_x and s_y are the starting locations of the drone in question. Each element (x,y,t) in the array represents the maximum possible utility for a path starting at the given starting location, ending at the location (x,y) and of length t. Another array is also used alongside U to track the path transitions. Then for each timestep starting at t=1 iterate over all elements in the array, updating the element to based on the max utility possible from the four possible paths coming from the orthogonal cells from the previous timestep. The path array is then updated based on the best path and the remaining three paths are pruned from the search space. The end result is an array which can be used to trace a path of length T-1 from all possible ending locations to the given starting location. Then we can find the path with the maximum utility from all the possible ending locations.

The single drone approach outlined above transitions well into a multiple drone approach. To preserve the polynomial runtime of the approach we plan the path for each drone individually and sequentially. However, when calculating the utility of the partial paths of each drone in the above process we include the full paths of all previous planned drones. In this way each drone is able to take into account what cells are going to be measured by the other drones. The runtime of this algorithm with the given utility function is $O(X*Y*T^2*D)$, where X, Y is the x, y dimensions of the utility map, T is the time horizon, and D is the number of drones to plan for.

In Figure 7, we show the results from this algorithm. We plan three drones with a time horizon of 60 steps, which translates to approximately 600km travelled for this specific utility map discretization.

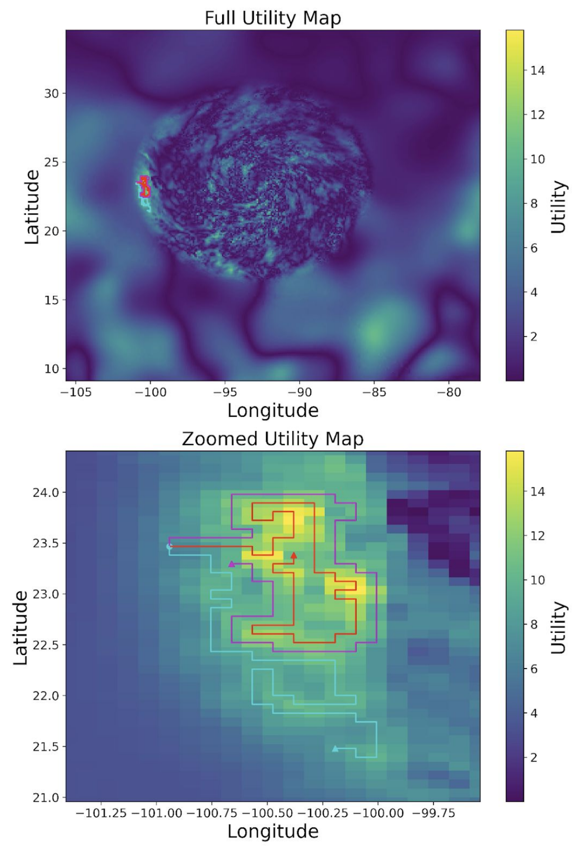

Figure 7: Planned drone paths to maximize the utility of measurements. Three drones are planned with a time horizon of 60 steps, equivalent to approximately 600km distance travelled. The top plot shows the full utility map and the bottom plot shows a zoomed in region where the drones are operating.

4 STATUS, DISCUSSION, RELATED WORK

This project is in early stages of prototyping and is still developing methods to evaluate any efficiency gains from this approach. We plan to evaluate the approach using a data denial experimental setup using historical and simulation data.

This project builds on prior work in which satellite measurements were directed based on alerts from other space and ground assets to track flooding [2] and volcanic activity [3]. However, these prior works did not estimate utility nor seek utility maximization observation but rather relied on much simpler observation triggers such as “when MODVOLC indicates a thermal emission, task EO-1 to observe” or “observe the flooded region with the largest areal surface water extent growth over baseline”.

5 FUTURE WORK

The current utility estimation approach produces a static map, limiting the possible utility functions for the utility maximization problems. This can be extended to produce a single utility value for a bag of points, accounting for correlation between each point. Because measurements can have positive and negative synergies, this is a more realistic model.

This change in the modularity of the utility function has significant ramifications for the space and drone planning elements of the effort. Future work will investigate heuristic methods for both space and drone planning. One approach is to use the modular utility estimates as a heuristic and to take feedback from the utility function in terms of which measurements contribute least to the joint utility.

The planning approaches will need to be extended to account for the conops of such missions. Including communication constraints, environmental considerations such as wind speed and drone deployment and recovery.

We will also investigate the combined space and drone planning problem. As space assets are typically controlled over longer timescales the interaction between these planning elements can be complex.

6 CONCLUSION

In this article we introduced an initial effort to apply an adaptive and model-driven sensing framework to the study of large scale storms. This framework is based on utility maximization with cost and operational constraints. The utility is derived from a high resolution science model rather than a trigger based optimization. The whole pipeline allows autonomous intelligent data collection and assimilation reducing the prediction uncertainties.

Acknowledgement

This work was performed at the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration.

References

[1] Torn D. R. and Hakim G. J. (2008) Ensemble-Based Sensitivity Analysis, *Mon. Wea. Rev.*, 136, 663-677.

[2] Chien, S. A.; Davies, A. G.; Doubleday, J.; Tran, D. Q.; Mclaren, D.; Chi, W.; and Maillard, A. Automated Volcano Monitoring Using Multiple Space and Ground Sensors. Journal of Aerospace Information Systems, 17:4: 214-228. 2020.

[3] Chien, S.; Mclaren, D.; Doubleday, J.; Tran, D.; Tanpipat, V.; and Chitradon, R. Using Taskable Remote Sensing in a Sensor Web for Thailand Flood Monitoring. Journal of Aerospace Information Systems, 16(3): 107-119. 2019.

[4] Zhang, F., M.Minamide, and E. E.Clothiaux, 2016: Potential impacts of assimilating all-sky infrared satellite radiances from GOES-R on convection-permitting analysis and prediction of tropical cyclones. *Geophys. Res. Lett.*, **43**, 2954–2963,

[5] Rappaport, E. N., J.-G. Jiing, C. W. Landsea, S. T. Murillo, and J. L. Franklin, 2012: The Joint Hurricane Test Bed: Its first decade of tropical cyclone research-to-operations activities reviewed. Bull. Amer. Meteor. Soc., 93, 371–380 (2012).

[6] Ancell, B. and Hakim, G.J., 2007. Comparing adjoint-and ensemble-sensitivity analysis with applications to observation targeting. Monthly Weather Review, 135(12), pp.4117-4134.

[7] Torn, R.D., 2014. The impact of targeted dropwindsonde observations on tropical cyclone intensity forecasts of four weak systems during PREDICT. Monthly Weather Review, 142(8), pp.2860-2878.

[8] Torn, R.D., 2010. Ensemble-based sensitivity analysis applied to African easterly waves. Weather and forecasting, 25(1), pp.61-78.

[9] Wick, G.A., Dunion, J.P., Black, P.G., Walker, J.R., Torn, R.D., Kren, A.C., Aksoy, A., Christophersen, H., Cucurull, L., Dahl, B. and English, J.M., 2020. NOAA's Sensing Hazards with Operational Unmanned Technology (SHOUT) Experiment Observations and Forecast Impacts. Bulletin of the American Meteorological Society, 101(7), pp.E968-E987.

[10] Hamill, T.M. and Snyder, C., 2002. Using improved background-error covariances from an ensemble Kalman filter for adaptive observations. Monthly weather review, 130(6), pp.1552-1572.

[11] Xie, B., Zhang, F., Zhang, Q., Poterjoy, J. and Weng, Y., 2013. Observing strategy and observation targeting for tropical cyclones using ensemble-based sensitivity analysis and data assimilation. Monthly weather review, 141(5), pp.1437-1453.

[12] Perron, L. and Furnon, V. 2020. OR-Tools. Google. https://developers.google.com/optimization/.

[13] Itai, A., Papadimitriou, C.H. and Szwarcfiter, J.L., 1982. Hamilton paths in grid graphs. SIAM Journal on Computing, 11(4), pp. 676-686.

[14] Zhang, F., M. Minamide, R. Nystrom, X. Chen, S.-J. Lin, L. Harris, 2019: Improving Harvey forecasts with next-generation weather satellites. *Bulletin of the American Meteorological Society*,100,doi:10.1175/BAMS-D-18-0149.1

[15] Xie B.; F. Zhang; Q. Zhang; J. Poterjoy; Y. Weng: Observing Strategy and Observation Targeting for Tropical Cyclones Using Ensemble-Based Sensitivity Analysis and Data Assimilation, *Mon. Wea. Rev.* (2013) **141** (5): 1437–1453.

[16] Singh A, Krause A, Guestrin C, Kaiser WJ, Batalin MA. Efficient planning of informative paths for multiple robots. InIJCAI 2007 Jan 6 (Vol. 7, pp. 2204-2211).

[17] Feillet D, Dejax P, Gendreau M. Traveling salesman problems with profits. Transportation science. 2005 May;39(2):188-205.