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FUSED DEEP LEARNING FOR HURRICANE TRACK FORECAST FROM REANALYSIS DATA

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***Abstract*—The forecast of hurricane trajectories is crucial for population and goods protection. In this work, we propose a fused neural network composed of one neural network using past trajectory data and of one convolutional neural network using reanalysis atmospheric wind fields images. This fused network is trained to estimate the longitude and latitude 6h-forecast of hurricanes and depressions from a large database from both hemispheres (more than 3000 storms since 1979). The average error distance (32.9km) is significantly lower than the baseline (46.5km), and the advantage of the fusion of the two networks is demonstrated.**

I. INTRODUCTION

Cyclones, hurricanes or typhoons are words designing the same phenomena: a rare and complex event characterized by strong winds surrounding a low pressure area. Their trajectory and intensity forecasts are crucial for the protection of the population and of their goods. However, their evolution depends on many factors at different scales and altitudes, which leads to difficulties in their modelling. Also, since the 1990s, storms have been more numerous, leading to both more representative and more consistent error statistics.

Today, the forecasts (track and intensity) are provided by numerous guidance models[1]. Dynamical models solve the physical equations governing motions in the atmosphere. While they can provide precise results, they are computationally demanding. Statistical models, in contrast, are based on historical relationships between storm behavior and various other parameters [1]. Current national forecasts are typically driven by consensus methods able to combine different dynamical models.

Statistical forecasting models still perform poorly with respect to dynamical models, even though the database made of past hurricanes is constantly growing. Machine learning methods, able for example to capture non-linearities and complex relations, have only been scarcely tested. However, they have recently shown their efficiency in a various number of other forecasting tasks. In particular, convolutional neural networks (CNNs) have raised attention as they are suited for large imaging data. In a promising study [2], a convolutional LSTM model was used for precipitation forecast. Another recent study predicts the evolution of sea surface temperature maps by combining CNNs with physical knowledge [3]. CNNs have also been used for the detection of extreme weather like hurricanes from patches of meteorological variables [4]. To our knowledge, only two preliminary studies have tackled hurricane forecast tracking using machine learning: the first one used random forests on local reanalysis histograms [5], however the mean error of 6h-forecasts does not seem to indicate satisfactory results (more than 60km). The second one used a sparse recurrent neural network from trajectory data [6], but it was tested on only 4 hurricanes and seems to yield large distance errors as well (the mean 6h-forecast error is 72km).

In this work, we propose a neural network architecture taking into account past trajectory data and reanalysis atmospheric wind fields images. This fused network estimates the longitude and latitude 6h-forecast of hurricanes and depressions from both hemispheres and different basins (more than 3000 storms since 1979). The average error distance reached (32.9km) is significantly lower than the baseline error (46.5km). We also demonstrate the advantage of using both sources of information simultaneously (wind and past trajectory).

II. THE MODEL

We aim at building an end-to-end model using two types of data (wind fields and history tracks) as input. For each time step of each storm, we want to independently estimate its future displacement. After presenting the data, we will show how we designed a convolutional neural network (CNN) to learn from the wind fields and

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[1]NHC track and intensity models, https://www.nhc.noaa.gov/modelsummary.shtml, Accessed: 2018-07-04.

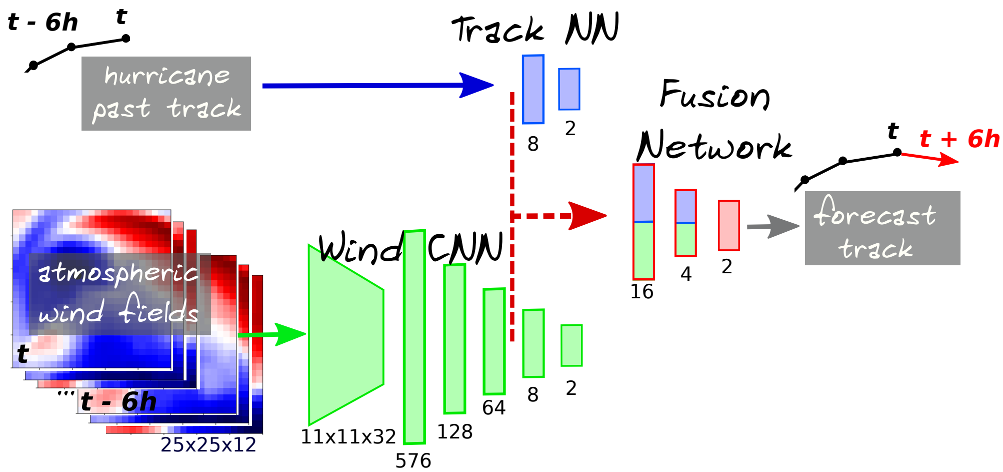

Fig. 1. General architecture: the two types of data are feeding two neural networks trained separately. The final fused network is re-trained before predicting the forecast track.

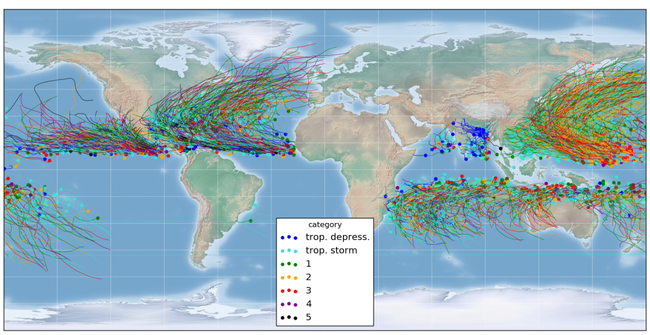

Fig. 2. Database: more than 3000 tropical/extra-tropical storm tracks since 1979. Dots = initial position, colors = maximal storm strength according to the Saffir-Simpson scale.

then improve the result by combining it with history tracks. Figure 1 summarizes the fusion pipeline that predicts the 6h storm displacement.

A. Data

The raw storm track data used in this study is composed of more than 3000 extra-tropical and tropical storm tracks since 1979 extracted from the NOAA database IBTrACS [7], see Figure 2. The tracks are defined by the 6-hourly center locations (latitude and longitude). They come from both hemispheres and the number of records per storm varies from 2 to 120 time steps. In total, the database counts more than 90 000 time steps.

The trajectory of a storm depends on large scale atmospheric flows. Thus, we extracted the wind fields of the neighborhood of the storm at every time step t from the ERA-interim reanalysis database [8]. Specifically, we extracted the u-wind and v-wind fields on a 25x25 degree grid centered on the current storm location, at 3 atmospheric pressure levels ($700/500/225hPa$). In order to capture the dynamics, we also extracted the wind fields measured at $t-6h$ at the same locations.

The choice of the 3 pressure levels was driven by statistical forecast models [1]. The reason why we focused on the wind parameter is that we applied a sparse feature selection technique (Automatic Relevance Determination, based on linear regression) over all available reanalysis fields, which highlighted the usefullness of wind.

B. Convolutional Neural Network for Wind Fields

Convolutional neural networks (CNN) are suited for non-linear learning with image-like data. They have already shown their efficiency in the climate informatics field [2], [3], [4]. The centered wind fields at different pressure levels at t and $t-6h$ can be seen as 12 images of size 25x25. We used as a guideline a typical CNN architecture alternating convolutional layers and maxpooling layers and added several fully connected layers at the end of the network [9]. To measure the improvements brought by increasing the CNN depth, we have designed 4 CNNs with the same number of neurons and varying depths. We observed very unobvious improvement on the result, so we chose the most shallow CNN with only 1 convolutional layer for computational reasons.

C. Neural Network for Past Tracks

Another important source of information is the previous displacements (latitude and longitude for $t-12h$

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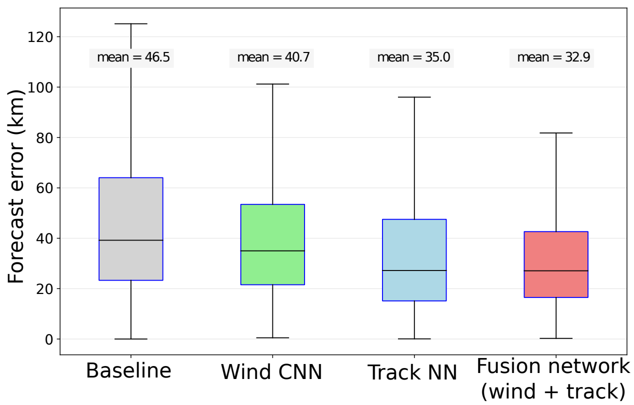

Fig. 3. 6h-forecast results on the test set (storms coming from all oceanic basins), in distance between predicted and real location. Baseline = previous displacement (going straight).

and $t - 6h$). We designed a small neural network (two small fully connected layers) able to learn the future track from this past track.

D. Fused Neural Network for both Wind and Tracks

Because of the different nature of the wind field image and of the past track data, it is not straightforward to mix them as a common input to a bigger network. Instead, we first train separately the wind field CNN and the small past track neural network (NN) previously mentioned, and then we fuse their two last layers, and re-train them together (see Figure 1).

E. Algorithmic Details

The storms were randomly separated in 3 sets as follows: train (60%) / valid (20%) / test (20%). Then, within each set, all time instants were treated independently. As a loss function (quantity to optimise), we used the mean square error (MSE) in kilometers between the forecast and the true storm location at $t + 6h$. We added an L2 penalty on the weights of the model (*coef.* $= 0.01$). The training was performed by the Adam optimizer. Our implementation uses PyTorch 4.0. The training and testing took less than 1 hour on 4 TitanX GPUs with data parallelism [10].

III. Experimental Evaluation

Figure 3 shows the 6h-forecast results on the test set in absolute distance error. We define the baseline prediction as equal to the last displacement (from $t-6h$ to t). We can see the improvement of fusing networks (mean error $\bar{e} = 32.9km$) with respect to the wind field CNN alone ($\bar{e} = 40.7km$) or the track neural network

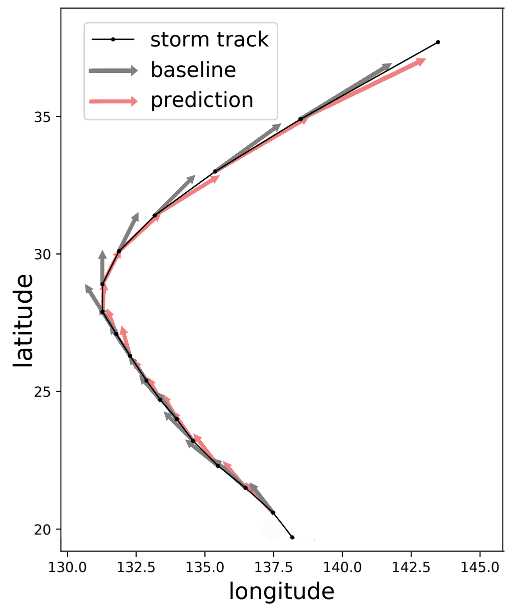

Fig. 4. Example of 6h-forecasts on one storm track. The baseline prediction is equal to the last 6h-displacement (going straight).

alone ($\bar{e} = 35km$). We have plotted in Figure 4 an example of 6h-forecasts on one storm track for the baseline and for our prediction (fusion networks). Our forecast predicts well, even in the case of change of direction or speed.

If these results are promising, some more long-term predictions are needed for a practical use. Moreover, current forecast models do not provide less than 24h-forecasts, which prevents us from comparing the results. With respect to the existing machine learning studies predicting 6h-forecasts [5], [6], we tend to perform better (error larger than 60km for both studies) and on a larger/more diverse dataset. Moreover, if we only look at hurricane time steps (without depressions), our mean prediction error drops to 25.8km. Depressions seem to be more difficult to predict: an explanation can be that they are smaller and more subject to local perturbations.

IV. Conclusion

We showed a promising deep learning framework for storm track forecasting. We demonstrated the benefit of coupling two types of data (past tracks and wind fields) in an efficient fusion model. Our results on a large database (90 000 time steps from 3000 storms) from different oceanic basins are showing 6h predictions with less than 33km error. Moreover, the error on only hurricane data points (without depressions) drops to 25.8km. We think that the use of such deep learning methods can help the current forecast modellers by providing a complementary prediction that could be integrated in some consensus methods.

REFERENCES

[1] M. DeMaria, M. Mainelli, L. K. Shay, J. A. Knaff, and J. Kaplan, "Further improvements to the statistical hurricane intensity prediction scheme (ships)," *Weather and Forecasting*, vol. 20, no. 4, pp. 531–543, 2005.

[2] S. Xingjian, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo, "Convolutional lstm network: A machine learning approach for precipitation nowcasting," in *Advances in neural information processing systems*, pp. 802–810, 2015.

[3] M. de Bezenac, A. Pajot, and P. Gallinari, "Deep learning for physical processes: Incorporating prior scientific knowledge," *arXiv preprint arXiv:1711.07970*, 2017.

[4] E. Racah, C. Beckham, T. Maharaj, S. E. Kahou, M. Prabhat, and C. Pal, "Extremeweather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events," in *Advances in Neural Information Processing Systems*, pp. 3402–3413, 2017.

[5] S. M. Liberge, S. Ba, P. Lenca, and R. Fablet, "Prévision de trajectoires de cyclones à l'aide de forêts aléatoires avec arbres de régression," in *Conférence internationale francophone sur l'extraction et la gestion des connaissances*, pp. 623–634, Hermann, 2011.

[6] M. Moradi Kordmahalleh, M. Gorji Sefidmazgi, and A. Homaifar, "A sparse recurrent neural network for trajectory prediction of atlantic hurricanes," in *Proceedings of the Genetic and Evolutionary Computation Conference 2016*, pp. 957–964, ACM, 2016.

[7] K. R. Knapp, M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann, "The international best track archive for climate stewardship (ibtracs) unifying tropical cyclone data," *Bulletin of the American Meteorological Society*, vol. 91, no. 3, pp. 363–376, 2010.

[8] D. P. Dee, S. M. Uppala, A. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. Balmaseda, G. Balsamo, d. P. Bauer, *et al.*, "The era-interim reanalysis: Configuration and performance of the data assimilation system," *Quarterly Journal of the royal meteorological society*, vol. 137, no. 656, pp. 553–597, 2011.

[9] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[10] A. Krizhevsky, "One weird trick for parallelizing convolutional neural networks," *arXiv preprint arXiv:1404.5997*, 2014.