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DEEP-HURRICANE-TRACKER: TRACKING EXTREME CLIMATE EVENTS

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***Abstract*—Existing approaches to tracking extreme climate events require an appropriate feature selection from physical variables and thresholds by human expertise. To predict extreme climate events, existing methods rely on physics-based climate simulations demanding tremendous computing cost. The recent progress in deep learning provides technical insights by capturing the nonlinear spatio-temporal interactions between a variety of physical variables. We propose two deep-learning-based models to track hurricane trajectories on massive scale climate reanalysis data. We address the spatio-temporal tracking as a mapping problem from time-series climate data to time-sequential hurricane heat maps using Convolutional LSTM (ConvLSTM) models. Our result shows that the proposed ConvLSTM-based regression models outperform conventional region-CNN-based detection methods.**

I. INTRODUCTION

Tracking extreme climate events is one of the most pressing and challenging problems. Research community has relied on physics-based simulation models for extreme climate event prediction [1], demanding tremendous computing cost. Recently, advances in machine learning open the door to more efficient and accurate multi-object tracking on various domains [2], [3], [4]. In this paper, we present a study on tracking extreme climate events using deep learning. We model the tracking problem as a regression problem, learning a mapping from time series climate variables to time series heat map of event probabilities. For this, we propose a variant of Convolutional LSTM (ConvLSTM) model, which effectively captures underlying spatio-temporal patterns existing in multivariate climate variables. The *Conv* part extracts spatial patterns, while the *LSTM* part captures the temporally evolving patterns. We compare against a simpler baseline using region-based Convolutional Neural Network (CNN) [5], that

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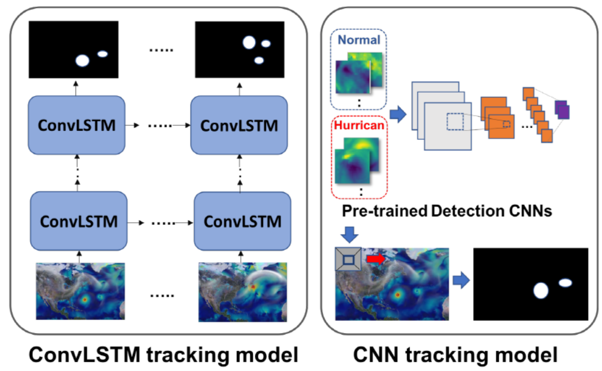

Fig. 1. Proposed Tracking Models

independently processes still images to detect events and integrates them by a predefined threshold. As a use-case, we apply our method to track tropical cyclones (hurricanes) from global map of climate video. With extensive experiment, we verify that the proposed ConvLSTM-based method effectively tracks and predicts hurricanes without requiring long history of hurricane trajectory.

II. TRACKING MODEL

The extreme climate event tracking is an example of the multi-object tracking problem, a task of locating multiple objects in a video (or a series of images), maintaining their identities, and yielding their individual trajectories given an input video [6]. Formally, the input $\mathbf{X} = \{\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_T\}$ consists of consecutive T climate images containing hurricane trajectories. There may be multiple trajectories in an input video, and each hurricane may start or end at any frame. Each $\mathbf{X}_i$, for $i = 1, 2, ..., T$, is an $m \times n$ 2-D climate image with multiple climate variables in each pixel. The label $\mathbf{y}_i$ is a set of k coordinates $\{\mathbf{y}_i^1, \mathbf{y}_i^2, ..., \mathbf{y}_i^k\}$ of hurricane centers existing in the corresponding input image $\mathbf{X}_i$. The number of hurricanes k in ground truth may vary for each input image. As we do not know the number of objects to be detected in each time frame, it is not straightforward to estimate $\hat{\mathbf{y}}_i$ as a set like $\mathbf{y}_i$. Instead, we represent both prediction and ground truth as heat maps. That is, we estimate a heat map $\hat{\mathbf{Y}}_i \in \mathbb{R}^{m\times n}$ with the probability of an hurricane observed in each pixel. Assuming that hurricanes are circular, we represent ground truth labels as a heat-map $\mathbf{Y}_i \in \mathbb{R}^{m\times n}$ by Gaussian mixtures centered on each element in $\mathbf{y}_i$. In this setting, we model the tracking problem as the pixel-wise regression problem from $\mathbf{X}$ to $\mathbf{Y}$. We introduce two approaches, a detection-based tracking using CNN and a regression model using ConvLSTM.

A. Detection-based Tracking using CNNs

As the hurricane detection can be solved using region-based CNNs in high precision, we detect hurricanes in each frame independently, and stitch the result to neighboring frames by some heuristics. Formally, we independently estimate a heat map $\mathbf{Y}_i$ from $\mathbf{X}_i$ for each $i = 1, ..., T$, ignoring temporal correlation between neighboring images. Figure 1 (right) shows our detection-based CNN model for hurricane tracking, consisting of two steps. First, we pre-train the detection CNN through a binary classification whether the input image patch contains a hurricane or not. The trained CNN model captures the essential characteristics of hurricanes. At the second step, we integrate overlapping image patches with their predictions into a single heat map that provides pixel-wise probability of hurricane on the entire image region. To speed up the convolution operation, we deploy fully convolutional networks (FCN) [7] instead of looping over the entire image with pre-trained feature. Our detection CNN consists of 6 layers, including 4 convolutional layers and 2 fully connected layers. Each convolutional layer has 64 5×5 feature maps, followed by a ReLU activation and a 2×2 max pooling. We combine all variables before feeding them into the model. After convolutional layers, softmax activation is used before the output.

B. Regression-based Tracking using ConvLSTM

We utilize ConvLSTM as a regression model for mapping from time-series climate images to time-series heat-map of hurricane events, effectively exploiting temporal information in addition to spatial relations. The ConvLSTM model is an extension of the conventional fully-connected LSTM by replacing with convolutional structures in both the input-to-state and state-to-state connections for fully capturing both spatial and temporal dependencies of the video. The ConvLSTM model has been effectively applied to spatio-temporal forecasting problems.

Figure 1 (left) shows our ConvLSTM model for hurricane tracking. Our model $f(\mathbf{X};\Theta)$ consists of multi-layered ConvLSTM with input-to-state and state-to-state kernels with size of 5×5, outputting consecutive time-series 2-D heat-map at each time step. Θ is a set of parameters. The input climate video consists of 3 channels while the output heat-map consists of a single channel. Therefore, to relate the feature maps to density map, we adopt filters all of size 3×1. We minimize the pixel-wise mean squared loss between the output heat-map $f(\mathbf{X};\Theta)$ and the ground-truth heat-map $\mathbf{Y}_{1:T}$:

$$L(\Theta) = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\|f(\mathbf{X}_{1:t};\Theta) - \mathbf{Y}_t\|_2^2, \quad (1)$$

where $\mathbf{X}_{1:t}$ takes the input climate image up to time t.

III. Experimental Settings

For dataset, we use 20-year run (from 1996 to 2015) of the *community atmospheric model v5 (CAM5)* climate reanalysis data. The ground truth labels of hurricane trajectories are obtained from TECA [8]. We use fixed time length of 30 hours ($T = 10$) with 3 variables, including zonal wind (U850), meridional wind (V850), and precipitation (PRECT), given their relevance to hurricane identification. In order to stay within memory constraints, we use only a sub-region of the entire global image as input with size of 160° (longitude) $\times$ 60° (latitude) (1°=111km) . We also reduce the original resolution of CAM5 by 2×2 max pooling. After reduction, the input image size is 128×256 with around 0.5°(55.5km) resolution.

To train the detection CNN, we collected 96,733 image patches sized 20×20 (representing $5^\circ \times 5^\circ$ (555 km)) centered on hurricanes for positive examples. We collected the same amount of random places with same size for negative examples. The labeling has been guided by tracking record obtained from TECA. The pre-trained detection model achieved test accuracy of 99.1%. For the evaluation metric, we report **precision** and **recall** based on nearest-neighbor mapping between the clusters of positive pixels from the output heat-map and those in the ground-truth heat-map. We also compute **Intersection of Union (IOU)** between 10×10 bounding boxes centered on detected hurricane centers. Among the pixels belonging to the same cluster, we take the maximum peak as its center.

IV. Result and Discussion

Tabel I compares two variants of regression-based models (4 layered and 5 layered) and the detection-based CNN model. We observe that the generated heat map with CNN is almost binary, meaning that most

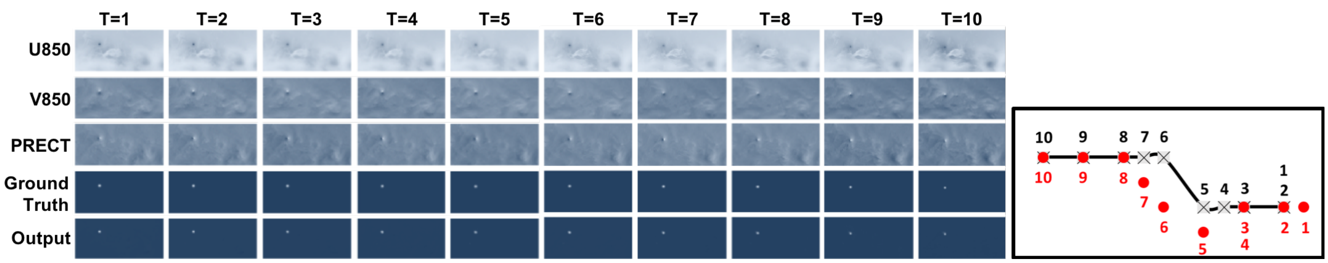

Fig. 2. Results from ConvLSTM tracking model. [Left] From the top, input channels (U850, V850, PRECT), ground truth, and output (frame size: $160^\circ \times 60^\circ$) [Right] Ground truth (black) and predicted (red) trajectories (frame size: $8^\circ \times 3^\circ$)

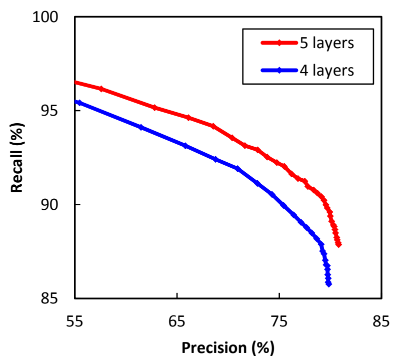

Fig. 3. Precision and Recall of ConvLSTM models.

TABLE I
ACCURACY OF TRACKING MODELS

Model	Precision	Recall	F1-score	IOU
ConvLSTM(4-layer)	44.2%	97.0%	60.8%	91.8%
ConvLSTM(5-layer)	46.9%	97.6%	63.3%	93.9%
CNNs(4-layer)	22.0%	98.7%	36.0%	59.0%

pixels are close to either 0 or 1. The detection-based CNN model achieves a high recall, but a significantly lower precision due to many false positives. In contrast, the heat maps generated by the regression-based models contain a wide range of values, so we vary the threshold (from 0.01 to 0.33) to trade-off precision and recall. Figure 3 shows the precision-recall curves for the ConvLSTM models with 4 and 5 layers. We observe that the deeper model performs consistently better than the other. For fair comparison against the detection-based model, we choose the threshold 0.01, achieving the highest recall level, reported in Tabel I. In every metric, we confirm that the ConvLSTM models outperform the detection-based CNN. The highest F1 score we achieved is 84.62% with the ConvLSTM model. Figure 2 and 4 shows example results from the ConvLSTM-based tracking model and from the CNN-based tracking model, respectively. Qualitatively, we observe that the ConvLSTM-based model produces heat-maps that are closest to the ground truth, while the CNN-based model provides a rough estimation with many false positives.

Fig. 4. Output from CNN tracking model at $T = 1$.

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