Attention-Hurricane: Attention-based Spatio-temporal Hurricane Path Prediction

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***Abstract*—Hurricane path prediction is considered as an important part of catastrophic modeling of extreme events. Typically, hurricane prediction algorithms tend to be complex and use a great number of parameters to ensure optimal accuracy. Furthermore, they require the use of high end hardware for calculation that is also time-costly. To solve the mentioned bottlenecks, we propose a deep Attention model that is designed to be efficient and deliver adequate accuracy in hurricane trajectory prediction. Our attention mechanism is use in input of our Recurrent Neural Network to increae the accuracy of hurricane trajectory predictions. To evaluate the prediction accuracy we have showcased the network accuracy in a similar dataset compare to previous state-of-art methods. The prelimnary results are promising as the networks ability to use attention mechanism gives hope for better trajectory prediciton.**

I. Introduction

Every year hurricanes produce loss and destruction in many places around the world. As the disruptive force of a hurricane comes from the wind speed of the rotating air and the rainfall that can cause disastrous flooding, the highest wind speeds are usually found near the hurricane center [1]. Furthermore, it found that hurricanes are becoming stronger, larger, and more destructive in the context of global warming [1]. The present work concentrates on tracks of hurricanes. As accuracy is only one measure about the prediction of natural disasters, speed and versatility play an important role as well. Forecasts should be done quickly and forecast tools should be able to react immediately on sudden changes. It's also reported that the current hurricane predictions of South Korea are done by conducting numerical simulations on a Cray XC40 supercomputer with 139,329 CPUs which holds aa huge amount of computational time. Not to mention that the maintenance costs for such expensive hardware are also very high. Therefore, an efficient forecast method that considers all these criteria is necessary [2]. Recently, the computer vision community has made important progress by using various pattern recognition techniques in visual object tracking, a task to locate a target object in a video, maintaining its identity and yielding its trajectory, given its initial position in the first frame [3]. Extreme hurricane event tracking is similar to visual object tracking, but it has unique, challenging aspects: hurricane events may be dependent on longer-term and wider-range Spatio-temporal dynamics among multiple experimental variables than the targets in visual object tracking do on RGB pixels. The target events are not often defined as rigid bodies, flexibly changing their shape with no clear boundary, and are difficult to visually separate them from each other. Thus, it is usually difficult to associate an object of interest with the correct one in consecutive frames. hurricane event data are normally

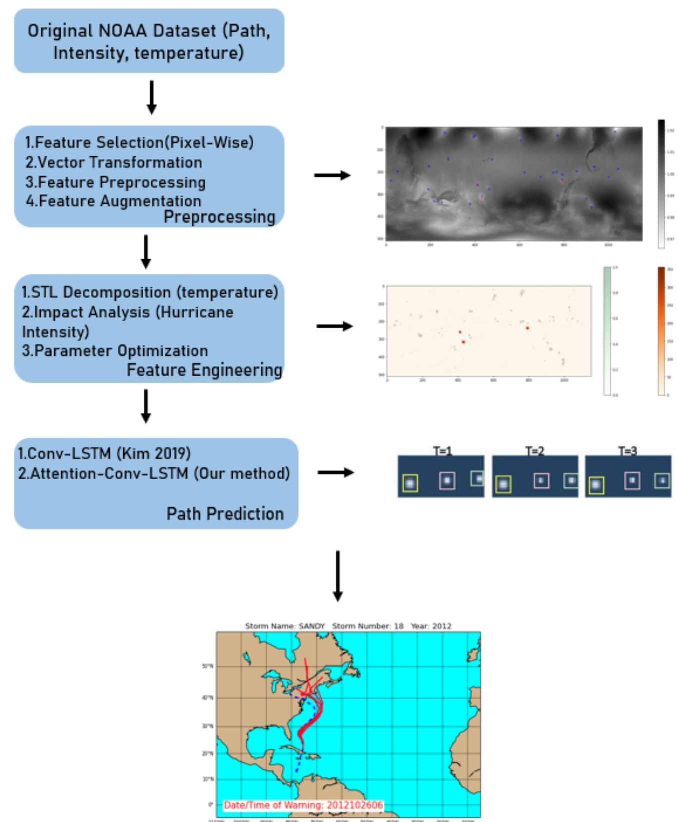


Fig. 1: The networks architecture follows this procedure. In our opinion the feature extraction is imporatant for attention mechansim. The networks input attention mechanism decides the weights of each input vector and our model will use both attention mechanism in the space-time vectors.

sparsely collected (both temporally and spatially), as it occurs rarely but requires special devices installed in the wild [4]. For example, the hurricane data we use in this paper are collected every three hours, sufficient time for a hurricane to move 350 km. That makes it difficult for us to assume the object would appear nearby in consecutive frames. Because of these challenges, a conventional tracking-by-detection method, which relies heavily on the amount of training data and detects the object mainly by its appearance but relatively neglects Spatio-temporal dynamics, is less suitable for this problem [2]. In this work, we introduce a simple but sound end-to-end model, suitable for the hurricane tracking problem. Particularly, the proposed model consists of two sub-modules, the (1) focus learning module to learn where and what to converge, and the (2) tracking module to track what we converged on. The focus learning module is designed to extract the latent feature of the target event from the first frame, given the initial image and the location of the target [2]. Given the representation of the target event, the tracking module predicts its location by localizing the learned feature of a target object in the subsequent frames. In both modules, we adopt ConvLSTM-based auto-encoder structure for the two subsequent reasons. First, it learns a mapping from time-series hurricane variables to a time-series density map with event possibilities, suffering less from a blurry boundary of hurricane events [5]. It compactly embeds the target's historical appearance change and movement in hidden states, capturing essential Spatio-temporal dynamics of the target.

Contributions.

. We implemanted seperate input self-attention mechanism in hurricane trajectory prediction (latitude and longitude).

. We showcased a uniform weight distribution of self-attention weights to increase the accuracy.

. We evaluated the networks performance on a similar dataset with previous state-of-art networks.

II. Background and Related Work

Tracking-by-detection approaches first detect candidates of the target mainly by using convolutional neural networks (CNNs). Afterward, the most likely candidate is chosen. When multiple target objects exist, each target needs to be associated with a distinct candidate. Among various CNN-based trackers, multi-domain CNN (MDNet) [6], [7] achieves the state-of-the-art performance on multiple datasets by learning discriminative features for instance classification To track a target without a rigid boundary or motion against the background, pixel-wise object tracking methods have advantages over tracking-by-detection approaches. Furthermore, [3] adopted gradient-boosted decision trees to estimate pixel-level annotation of a segmentation mask.

In the works done by [1], a trained GAN is employed to produce a track of a hurricane for which the GAN was not trained. The predicted track image of a hurricane favorably identifies the future position of the hurricane center as well as the deformed cloud formations. In the work of [6] and [7] various existing forecast techniques are listed. Including analog forecasts, features of the hurricanes are compared to all previous storms in the same region and the movement is derived from past events the steering current is estimated by analyizing the winds at certain locations and altitudes. The statistical technique uses regression analyses, whereas the dynamical technique uses numerical modeling and simulation. The persistence method allows short-term predictions but relies on the cyclone to keep its recent track. Satellite-based techniques use satellite pictures to make forecasts of the track and intensity of tropical cyclones based on cloud patterns. To best of our knowledge, [4] first used satellite pictures of tropical cyclones for track forecast with the help of neural networks. But pictures did not work as input data for the network. In a pre-processing step, data like the Dvorak number, the maximum wind speed or the cyclone's position were derived from pictures and fed to the network for a time-series prediction. But pictures did not function as input data for the network. In a pre-processing step, data like the Dvorak number, the maximum wind speed or the cyclone's position were extracted from pictures and fed to the network for a time-series prediction. Furthermore, [8] was the first who study which used satellite pictures as input data for a neural network. The network favorably detected the shape of a hurricane and predicted the future movement direction. Also, [6] have used a sparse recurrent neural network (RNN) to predict trajectories of cyclones coming from the The Atlantic Ocean or the Caribbean Sea, also known as hurricanes. They used dynamic time warping (DTW), which compares the trajectory of a target hurricane to all hurricanes of a dataset. For the forecast process, only hurricanes that have connections in trajectories to that of the target hurricane were used. One disadvantage is that they assumed monotonic behavior, which means that a hurricane never comes back to a position where it was before. In reality, this is not always the case

Recurrent Neural Networks (RNN) have gain momentum as their architecture use more parameters and deep algorithms have more tools to predict in various fields such as financial, medical and trajectories such as hurricanes. To best of our knowledge [6] used an RNN to predict hurricane trajectories, but instead of assuming monotonic behavior they examined all types of hurricanes. They used a grid-based RNN that takes the wind speed, latitudinal and longitudinal coordinates, the angle of travel, and the grid identification estimate from past movements of the hurricane as inputs. With the grid identification number, spatial relations on a map were learned. Their forecasts could achieve better accuracy than the results of [7], [9] utilized matrix neural networks (MNNs) for predicting trajectories of cyclones that occurred in the South Indian ocean. It also stated that MNNs suit is better for the task of hurricane trajectory prediction than RNNs because MNNs can preserve spatial data of cyclone tracks.

In the previous research, deep learning methods were used to identify the center of a hurricane in a satellite image or to predict a trajectory of a cyclone using discrete meteorological data without cloud pictures. None of the previous studies

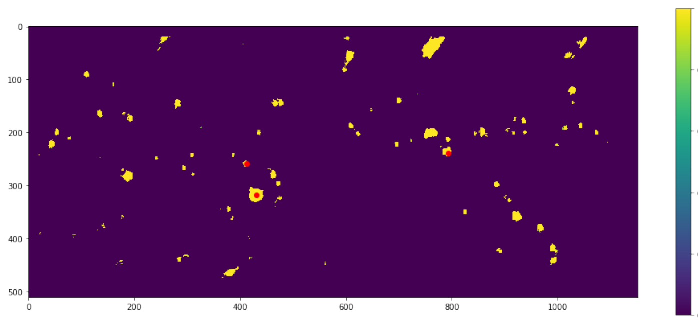


Fig. 2: The x-axis is lattidude and y-axis is longitude. Input Attention mechanism: The use of attention mechanism in input (2D space) will add a new dimension of weights for 2D dimensions. The networks training phase will optimize the weights to for adding space attention on parts of images that are will improve the accuracy. Our network will use attention weight optimization will be made on both latitude and longitude seperately.

using neural-networks reported the capability of predicting both the coordinate of a hurricane center and future shape of cloud compositions around the hurricane [1] a generative adversarial network (GAN) is used for both tasks. As an input, it uses chronologically ordered satellite pictures from the past and as an output, it creates pictures that show the hurricane hours ahead. A conceivable alternative to the present approach of predicting the coordinate of a hurricane center can be predicting the direction and the speed of a hurricane, from which, afterward, the future position of the hurricane the center is determined. However, to predict the moving direction and the speed of a hurricane using a GAN, it is still necessary first to forecast the hurricane center, where the direction and the speed of the hurricane are defined. The present GAN employs satellite cloud pictures along with a marked hurricane center as the input set, but without explicit data about the moving direction or the speeds at the hurricane center.

Recently, convolutional LSTM (ConvLSTM) [30] has been widely used to handle spatio-temporal properties in analyizing the video data, e.g., precipitation forecasting [6], motion prediction [5], pixel-wise video prediction [10], crowd counting [8], and segmentation-based tracking [11]. Conventional extreme hurricane event detection and tracking methods rely on a number of mathematical simulation-based methods, including an ensemble of multiple prediction models or multi-scale prediction systems Also, ConvLSTM [3] and incremental neural networks were proposed to predict the future trajectory of hurricanes and cyclones. Region CNNs were used to classify different types of extreme hurricane events. Most existing approaches, however, have not addressed unique challenges to manage sparse hurricane data covering a wide geographic range for an extended period. In this work, we tackle the unique challenges of the hurricane event tracking problem introduced in Section 1 with the ConvLSTMs-variant model, which is specially designed to seize a wide range of Spatio-temporal properties.

In previous studies, various machine learning models have been used to predict hurricane paths

In [2], the authors treated the hurricane path as a time-series problem that can be solved with 5 a simple RNN model. One limitation of this model is not using the hurricane path data with its 6 intensity accordingly. The model simply does not know what is the hurricane severity at each time 7 step. However, the intensity of the hurricane holds great data about the speed, path and other 8 factors that are important in accurate path prediction [1].

III. Methodology

As mentioned in the limitation section, the simple state-of-art Conv-LSTM architecture does not have enough features to deliver a reliable prediction. Using only the observed atmosphere images will not result in a comprehensive model that can be used. In our study, we intend to tackle these limitations by using a more comprehensive dataset from the National Oceanic and Atmospheric Administration [12]. In combination with a better feature vector, we intend to improve the previous state-of-art architecture (Conv-LSTM) by using an input attention mechanism.

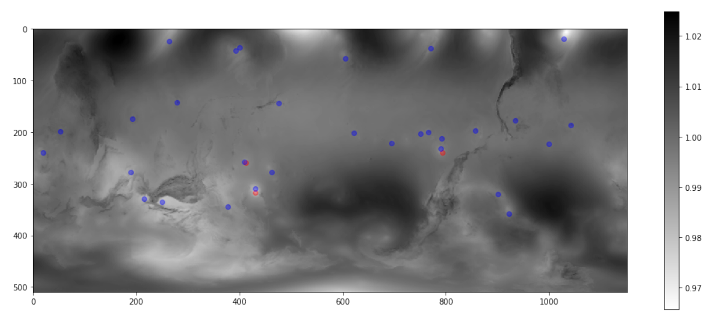


Fig. 3: World map has been used in our input for 2D represntation of network. The 2D image of the world holds great value in terms of land, sea, and position of hurricanes which was has not been under investigation by prevoius studies [3], [7], [8].

The proposed study intends to tackle the problem of reliably predicting the trajectory of a hurricane using test and training data. To solve this problem, we have using the architecture introduced in 1, which is known to be effective in operations involving spatial data. Since the deep neural network cells are LSTMs, a multiplication of convolution operations performed at each gate in the LSTM cell. As a result, it can capture underlying spatial features from multi-dimensional data.

A. Attention Mechanism

Motivated by the cognitive neuroscience, researchers have introduced attention mechanisms into the coding-decoding

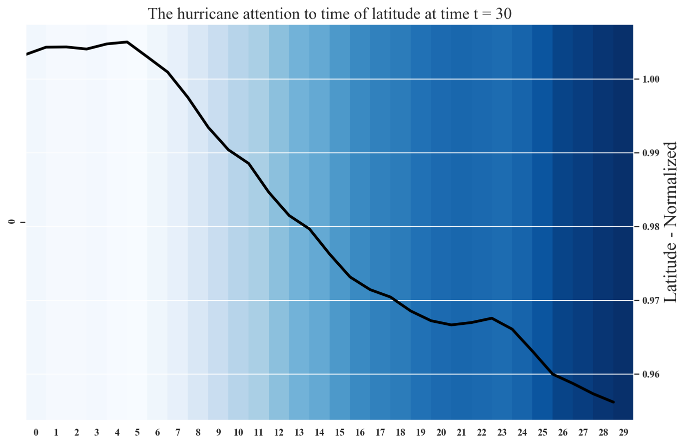


Fig. 4: Lattidude Input Attention mechanism: During the training a time window of 30 inputs will be fed into the network consecutively. In this sample, the networks attention weights will be higher on latter part of the input to predict the next location. The y-axis will hold only the lattitude value.

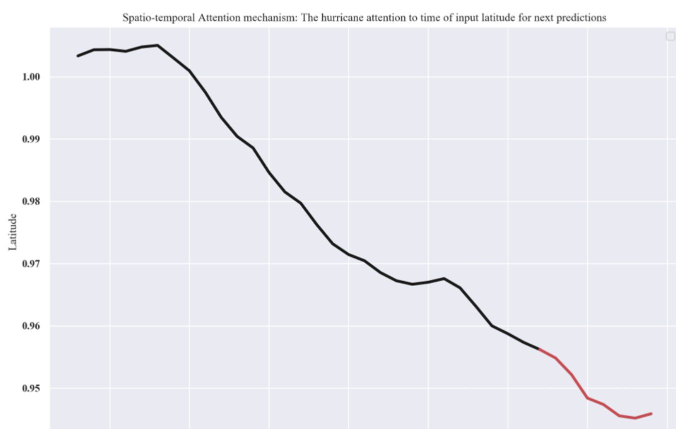


Fig. 5: Lattidude prediction based on previous attention: The models prediction is simlar to latest part of attention where the attention weights were made in lattidude decrease (Lattidude predicted to get lower).

framework of neural networks. Moreover, looking at the Figure 2, the attention mechanisms can better select input sequences and encode semantics in long-term memory to improve the information processing capabilities of neural multi-order [8].

The attention weights are seen as below:

$$W = \left(W^1, W^2, \ldots, W^L\right) \tag{1}$$

Given input as a a series of hurricane locations, the attention weights will be implemanted as below:

$$\tilde{X}_t = \left(x_t^1 W^1, x_t^2 W^2, \ldots, x_t^L W^L\right) \tag{2}$$

Lastly, the following will be fed into the our 2-layered LSTM network.

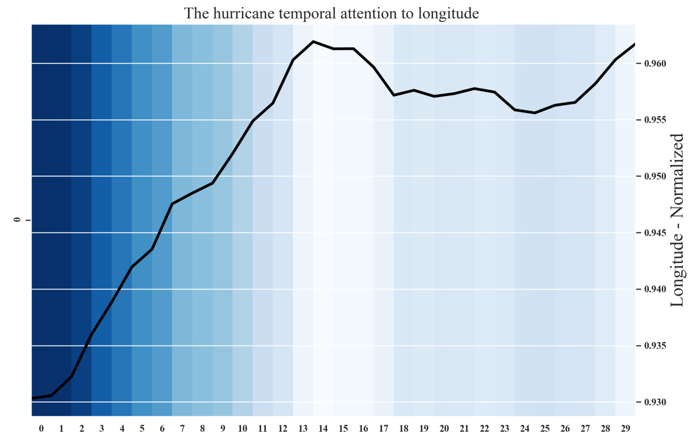


Fig. 6: Longitude prediction attention distribution: The attention weights are more higher at the beginning of the input (temporal).

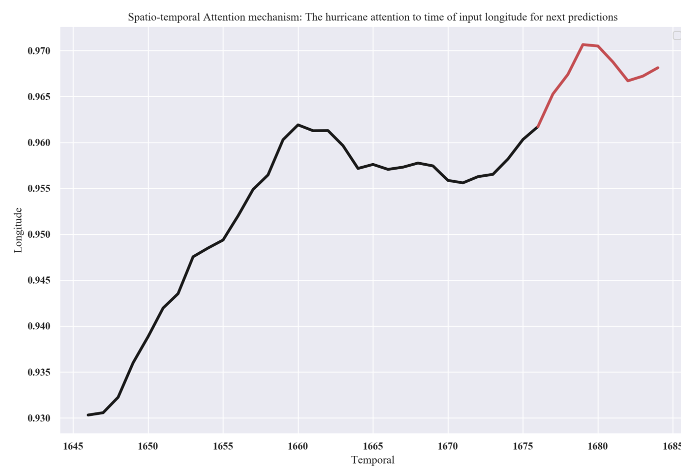


Fig. 7: Longitude prediction based on previous attention: The models prediction is simlar to beginnin part of attention.

$$\tilde{X} = \left(\tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_T\right) \tag{3}$$

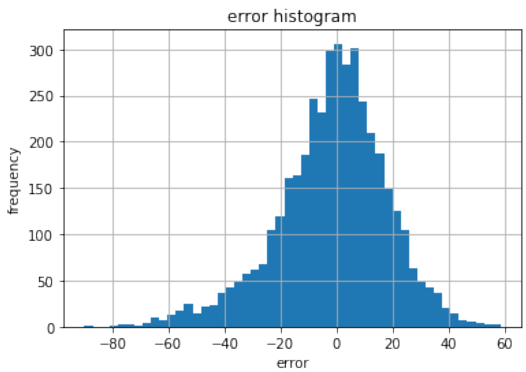
IV. Experiments and Discussion

In this secion we discuss the performance of Attention-Hurricane network in comparison with previous work that was discussed in realted works section.

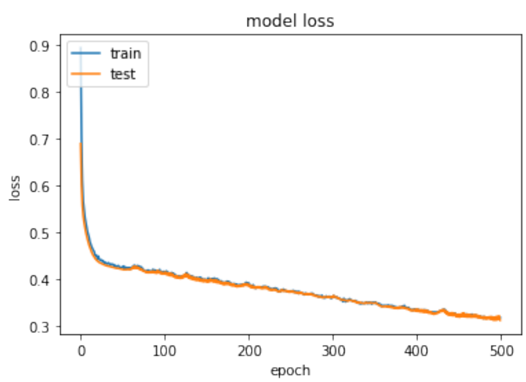
Parameter	Value
Input_Dim	(1,1,1,1)
Hidden_Layers	80
RNN_layers	2
LSTM layer 1	Dropout = 0.1
LSTM layer 2	Dropout = 0.2

TABLE I: The 2-layer attention network hyperparameters. The network has been trained from scratch.

As shown in figure 8, the other way to increase the accuracy of our prediction is to improve the optimization of our loss function. During the training phase, the network will improve its precision by adjusting its weighted cross-entropy loss for a sequence of inputs by calcuating their loss for wind 8, latitude 9, and longitude 10.



(a) Histogram of wind errors

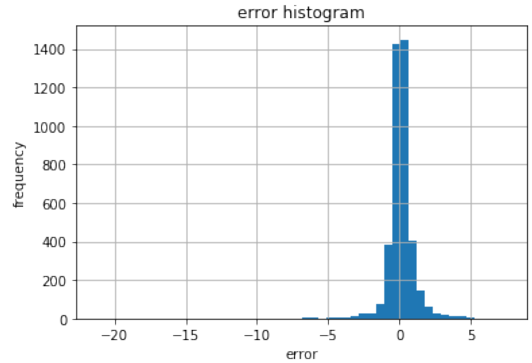


(b) Wind training and validation loss

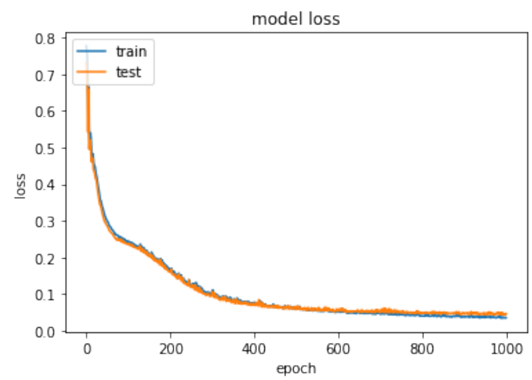
Fig. 8: Wind predciton loss histogram. Due to the sudden changes in wind speed (Category 1-5 hurricanes), the prediction of wind speed produces higher loss than the location of the hurricane. This is due to the random nature of windspeed.

Moving on to the trajectory prediction, the networks training and validation data has been split to 80-20 where the first 80 percent of the data is being trained on the network. It must be mentioned that we are using the same hurricane data as previous works that include previous hurricanes such as Andrew and Mathew.

Looking at figure 9, the networks prediction error for latitude is much lower than wind prediction. This is mainly due the effectiveness of attention mechansim in spatio space where the network pays only attention to the most important features of 2D space rather than considering the whole input. The weight tranining of attention mechansim has been shown in figure 4 where the weight training and optimizaiton of attention mechanism holds great value in reducing the prediction error.



(a) Histogram of latitude errors



(b) Latitude training and validation loss

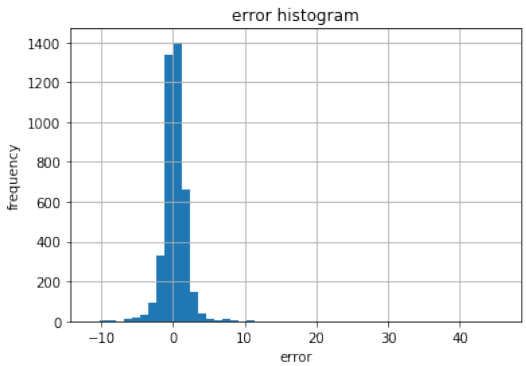
Fig. 9: Training .Figure B shows training and validation loss during learning with for 1000 epochs.

Next, looking at figure 10, the longitude will also demonstrated adequate loss after 1000 epoch training. Although the compuatation of attention mechanism is much higher than the previous studies such as [3] and [13], the network accuracy would increase and the number of network parameters can be reduced greatly.

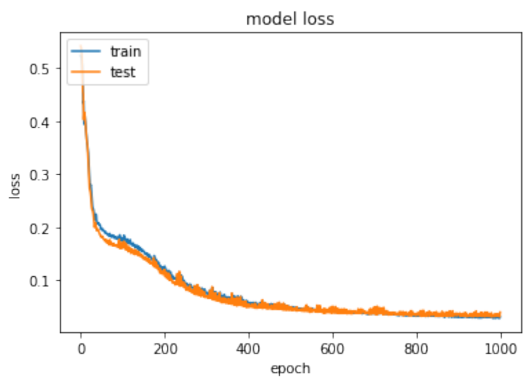
Model	IOU: 0.1	IOU: 0.5
Detection-based CNN [7]	14.78%	12.26%
3D Conv Encoder-decoder [8]	22.65%	15.53%
2 layered ConvLSTM [14]	88.96%	87.32%
3 layered ConvLSTM [14]	93.77%	92.18%
4 layered ConvLSTM [14]	92.58%	90.87%
5 layered ConvLSTM [14]	93.49%	91.93%
2 layered Attention-Hurricane(our)	92.36%	90.45%

TABLE II: Comparison of AvgP for trajectory prediction models. The [12] dataset has been used in evaluation. Our models performance is higher when fewer layers of ConvLSTM has been used.

Lastly, in II, the networks performance was compared to the reported accuracy of previous studies.



(a) Histogram of longitude errors



(b) Longitude training and validation loss

Fig. 10: Networks performance in longitude prediction. Figure B shows training and validation loss during learning with for 1000 epochs.

Our focus was set on using less reccurent layers in the architecture so that the attention model utilizes its weights in the procedure.

V. Conclusion & Future Work

In this work, we have analyzed the hurricane trajectory data and evaluated its correlation with extreme natural events such as hurricanes. Furthermore we used various forecasting methods (Statistical - Machine Learning) to find the adequate forecasting system that is sensitive to irregular events. Next, we showcased the use of attention mechanism in hurricane trajectory prediction. Since implemanting the pixel-wise spatio-temporal requires weight loss optimization of attention, our network implemantion was faced by a set of constraints we were not able to fully showcase the accuracy of our performance by fine-tuning. However, for future work, we are looking to include a more comprehensive analysis of our methods efficiency in compared with baseline methods that is runned locally on the same machine as ours. dataset and provide a better accuracy. Also, note that the pixel-wise attention is chosen to be used in future prediction and will be evaluated to our previous baselines.

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