Wind Engineering Joint Usage/Research Center
FY2024 Research Result Report

Research Field: Wind Hazard Mitigation
Research Year: FY2024
Research Number: 24242002
Research Theme: AI/ML based Tornado Speed Determination and Prediction from the Windborne Debris Captured in the Tornado, using Video Processing Techniques

Representative Researcher: Prof. Sudha Radhika (BITS Pilani, Hyderabad campus) and Prof. Masahiro Matsui, (TPU/WERC member, PI)

Budget [FY2024]: 160,000 Yen

1. **Research Aim**: This research aims to estimate and predict the speed of a tornado by using object tracking techniques in Machine Learning on from the captured tornado videos. The tracking object will be any wind-borne debris captured inside the moving tornado and this object will essentially have the same rotation speed as the tornado. To increase the database to fine tune the speed estimation and prediction of Tornado speed using AI/ML algorithms, TPU Wind Tunnel Facility will be utilized. Fine-tuning object detection and tracking using LSTM (Long Short-Term Memory) will increase the accuracy of speed calculation.

2. **Research Method**: The object, whose speed is to be captured comes into focus when it moves in the tornado's outermost region. A tornado is a very dense phenomenon, and the object, irrespective of its size, gets occluded due to thick layers of dust and water droplets. The tracking precision depends on precise and accurate object detection. Any video has two kinds of information: spatial and temporal. The spatial information deals with the position and characteristics of the object of interest, while the temporal information deals with the change in environment and object's motion with time. As the input is a video, using a Recurrent Neural Network with CNN makes sense as the input is a video. CNNs are used to compute image data, and RNNs are used to study the sequential characteristics of data.

   The entire process is shown in detail is shown in Fig. 1

   Thus the objectives are

   - To track the object (wind-borne debris) captured inside the moving tornado and (Assuming this object will essentially have the same rotation speed as the tornado)
   - To increase the database to fine tune the speed estimation and prediction of Tornado speed using AI/ML algorithms, TPU Wind Tunnel Facility will be utilized.
   - To identify the tracking using Python (platform independent software)

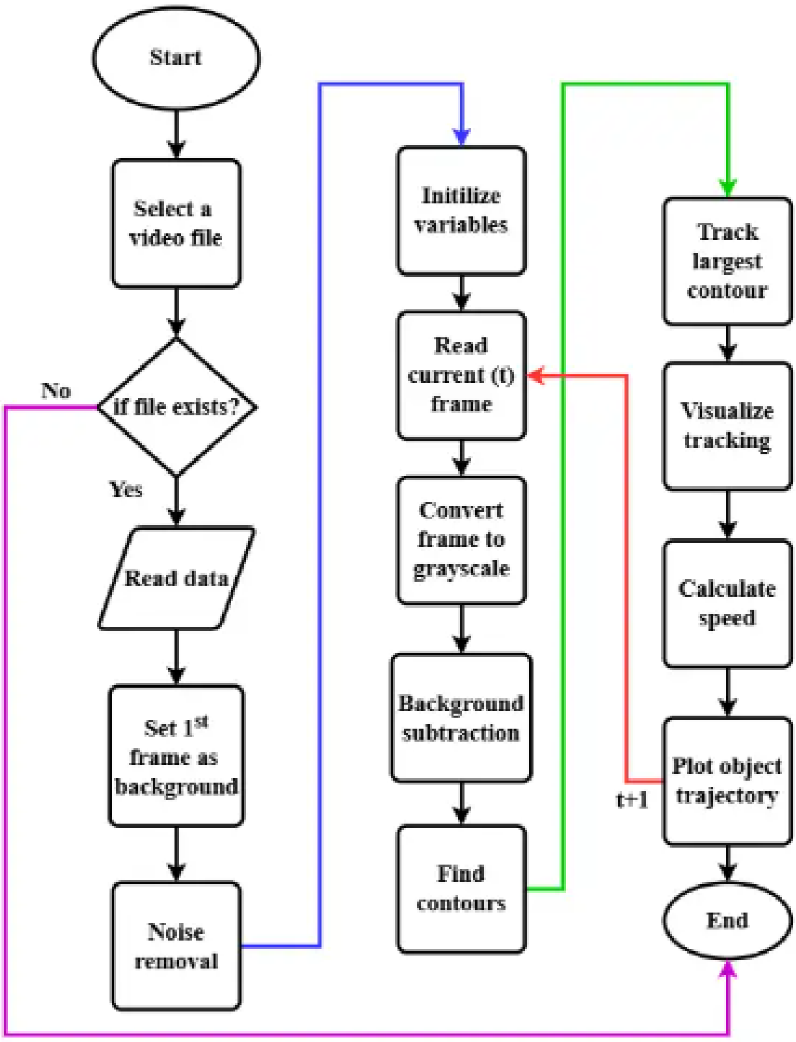


Fig.1

Data augmentation is widely employed in Machine Learning and computer vision. It aims to enhance dataset diversity by introducing a range of transformations to the existing data. The primary objective of data augmentation is to generate extra training instances that represent variations of the original data, all while retaining the core information. This practice is instrumental in enhancing the performance of machine learning models. Data augmentation is very significant for our use case. The reference object will be a random object stuck in the tornado. For precise tracking, we need ample images of that object so that the LSTM model can be trained with them. The project deals with 'Image Data Augmentation.' Image data augmentation can be achieved by rotation, zooming, cropping, flipping, resizing, changing brightness, adding contrasts, applying filters, RGB channel change, or even adding noise to the data in hand. All the laterally shot video frames are separated and fed to the data augmentation model for the operations discussed above. Data augmentation for images is not recommended when the data set is minimal, like 150-200 images. Using such a small data set will give biased outputs.

Since the object stuck could be random, we must train the images from our database. For training, the augmented data set will be utilized. The augmented images are divided into two folders: training and testing datasets. Using “Labeling,” we must manually annotate all the objects in the augmented images. Labeling is an annotation tool specially used to label bound objects in images. We can Extend the tracking algorithm to handle multiple objects simultaneously. This can be achieved by modifying the object detection and tracking pipeline to detect and track multiple objects within the tornado simultaneously. In order to improve the precision of object detection within the tornado, fine-tuning the object detection model with a specialized dataset that includes various scenarios of occlusion and debris movement would be beneficial. This can help the model better understand the unique challenges posed by the dense phenomenon of a tornado. We can retrieve the total number of frames in the video and its frames per second (FPS), and then proceed to save every other frame from the video as JPEG images. This effectively extracts every other frame from the video and save them as JPEG images. We can save frames at a different interval, and can adjust the condition accordingly.

The work has been performed in

1. DippMotion 3D Software
2. MATLAB Coding
3. Python Coding

Video capture for the same has been taken during in the Tornado simulator Facility at TPU

Three cases of boundary conditions 1, 2, and 3 have been observed as shown in Fig. 2(a), 2(b), 2(c), respectively.

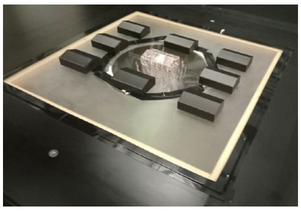
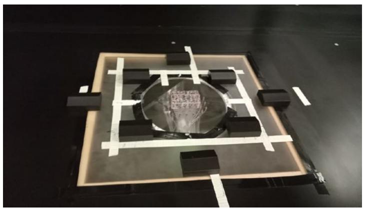
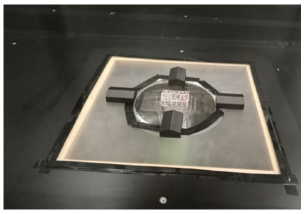




Fig 2(a) **Fig 2(b)** **Fig 2(c)**

The wind borne debris has been modelled using sponge foam material and is divided into the six weight categories as shown in Fig.3(a) and (b).

1	WINDOW1	W1
2	WINDOW2	W2
3	DOOR	W3
4	BROKEN ROOF	W4
5	ROOF1	W5
6	ROOF2	W6

Fig.3(a)

Fig. 3(b)

The density of the sponge foam material used in the experiment is determined by measuring the weight and the volume of each model and the density values are as shown in Table 1. The average density of the material is observed as 11.08kg/m^3.

	Weight in gm	Volume in mm3	Density in kg/m3
W1	0.006	625	9.6
W2	0.008	625	12.8
W3	0.014	1250	11.2
W4	0.026	2500	10.4
W5	0.046	4000	11.5
W6	0.055	5000	11

Table.1

The trajectory for each debris model is plotted using ML based image processing algorithms and the velocity was calculated for each case. The results are given next section. To integrate LSTM into the project for tracking objects within a tornado, we preprocess image frames using CNNs to extract spatial features. These features are then fed into LSTM to model the temporal dynamics of object movements over time. Training the hybrid CNN-LSTM architecture with augmented datasets allows the model to learn diverse variations of object trajectories and occlusion patterns. Once trained, the model performs object detection and trajectory prediction within tornado videos, providing valuable insights into tornado dynamics. Continuous evaluation and improvement ensure the model's effectiveness in real-world scenarios, supporting real-time tracking and monitoring of tornado activity.

Facility usage at TPU: Usage of Tornado simulator facility at TPU helped in in acquiring video databases for implementing the AI/ML model which in turn gave us more accurate estimation and prediction of the speed. The usage of high-speed cameras for capturing videos provided a comparison of the speed measurement using the proposed AI/ML based algorithm with the DippMotion 3D.

3. Research Result

3.1 DippMotion 3D video capture

The tracking of thermocol balls (used as debris here) is observed in Fig.4(a) and Fig.4(b)

Fig.4(a)

Fig.4(b)

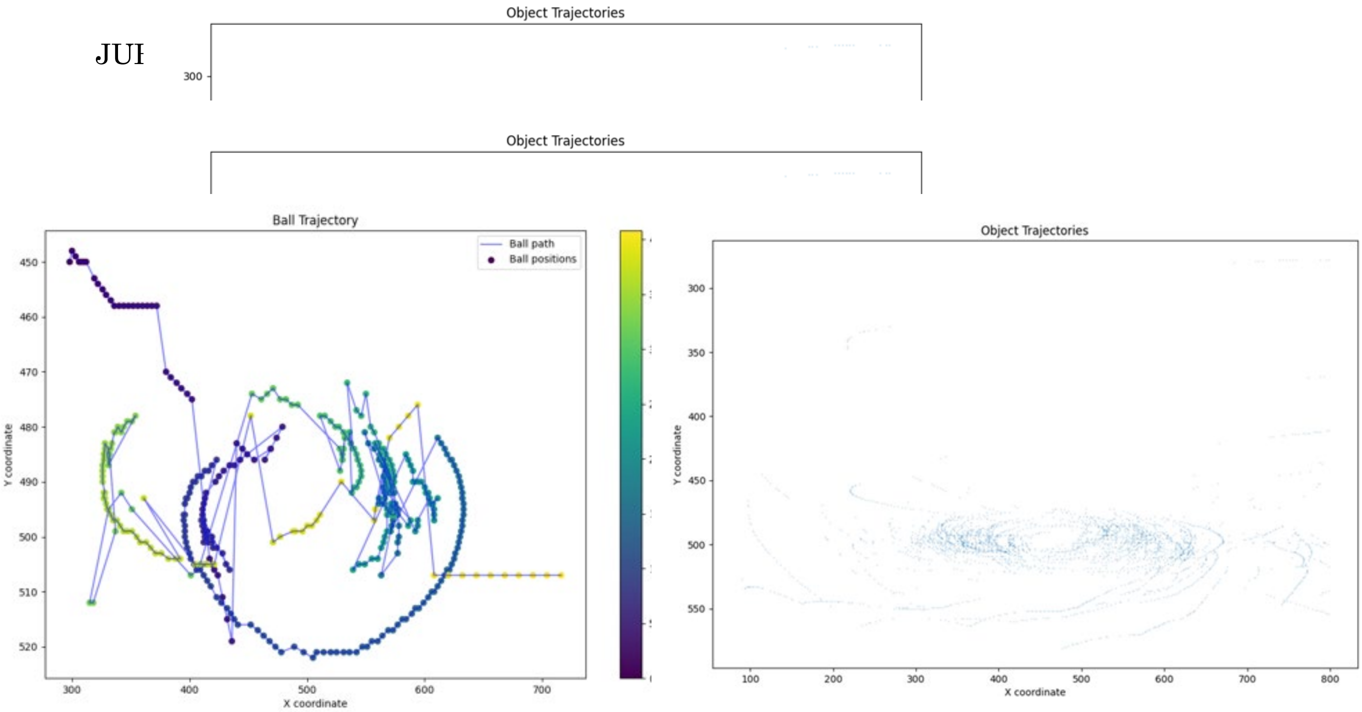


Fig.5

Measurement of tornado speed both instantaneous and average speed is calculated and the results are plotted in Fig.6. These results also presented the motion or positioning of the tornado centre as well.

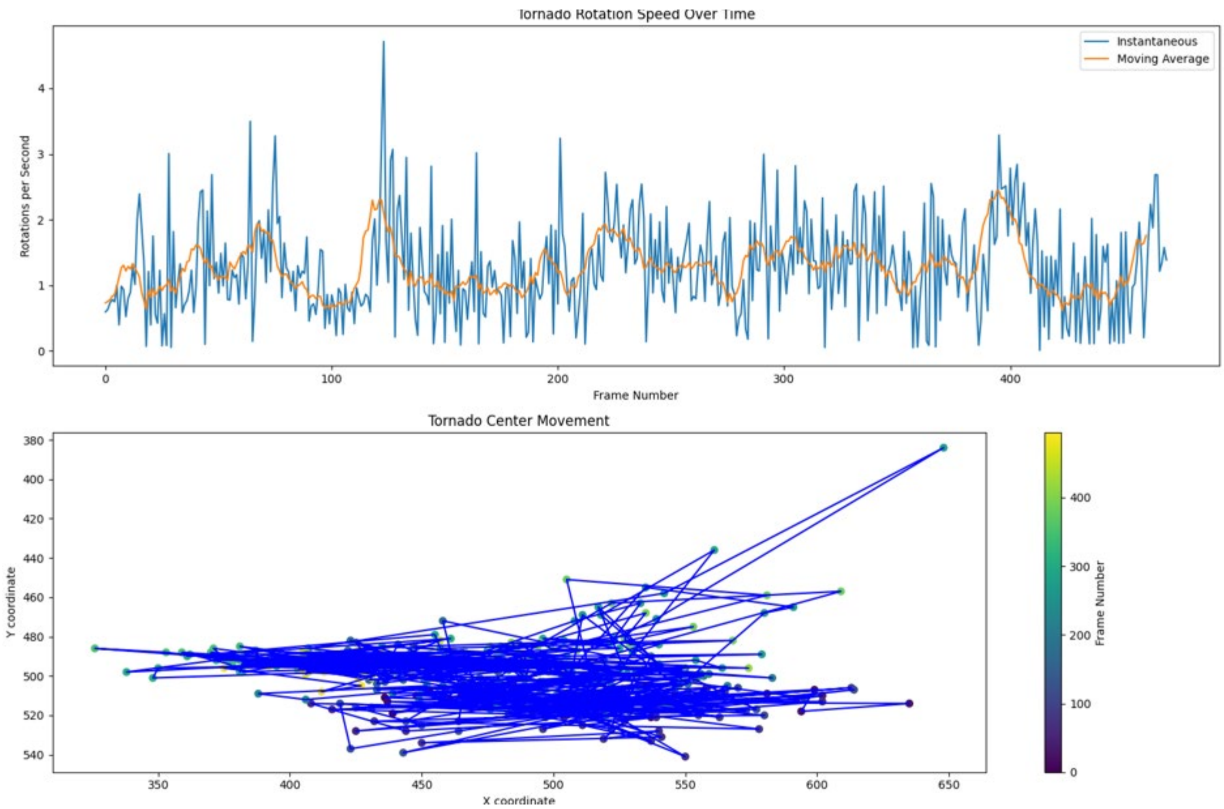


Fig.6

3.2 Tornado simulator results

In the tornado simulator the tornado trajectories for all the six wind borne debris cases are plotted and velocities are measured using both MATLAB programing as well as Python coding. Python provides and independent platform to trace the trajectories, which can be further extended for making a user-friendly GUI (Graphical User Interface). The plotted trajectories in MATLAB is shown in Fig. 7 and in Python is shown in Fig.8.

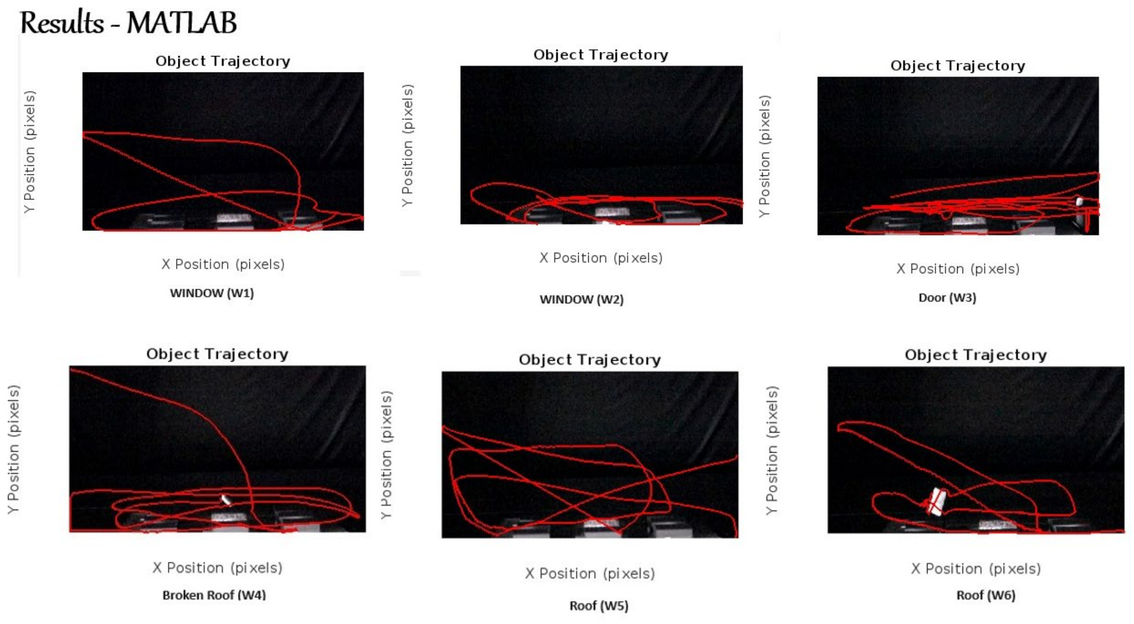


Fig.7

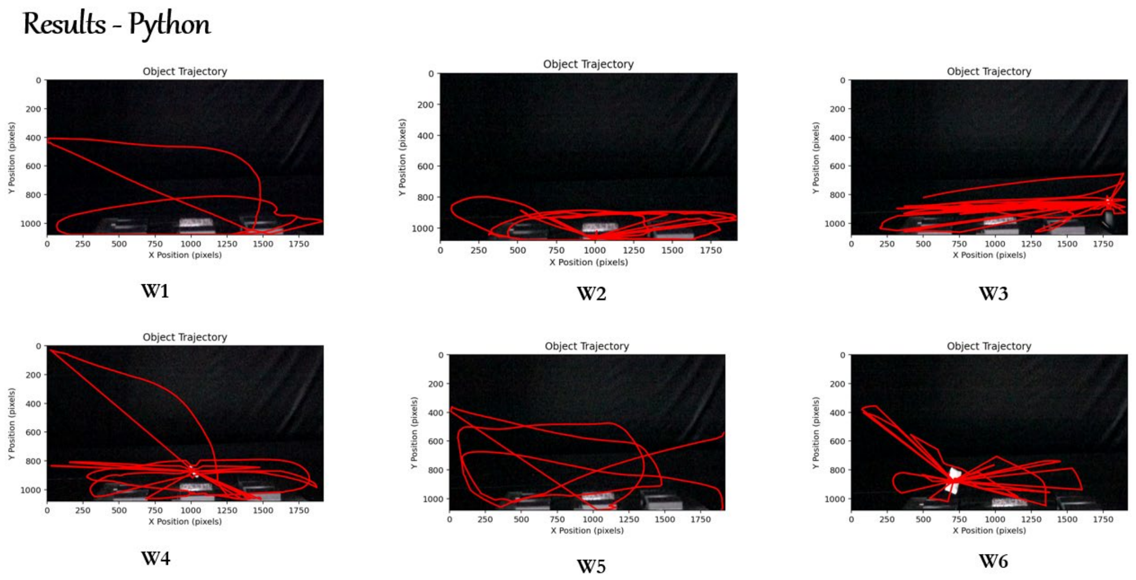


Fig.8

Similar results for 2nd boundary conditions are also plotted and the speed are measured and the results are shown in Table 2

Table 2

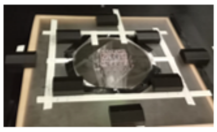
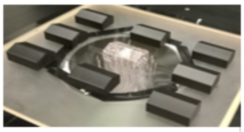
Models	Average speed m/s	Density in kg/m3
W1	4.85	9.6
W2	3.15	12.8
W3	4.8	11.2
W4	5.2	10.4
W5	5.27	11.5
W6	2.83	11
Average Speed	4.35	

Object	Velocity (m/s)	Computation Time (s) – i5-8th Gen Intel Processor
W1	4.63	103.9
W2	5.58	90.9
W3	4.70	95.5
W4	5.02	97.0
W5	5.15	93.0
W6	4.07	100.5

Table 2 (a) in MATLAB and Table 2 (b) in Python for boundary condition 1

4. Conclusion

Thus, the object (wind-borne debris) captured inside the moving tornado is tracked and (Assuming this object will essentially have the same rotation speed as the tornado) speed is estimated. The program is coded both in MATLAB and Python and two boundary conditions are considered and the final speed estimation is displayed in Table 3. Usage of the Tornado simulator facility in TPU help to collect a huge video database to fine tune the speed estimation and prediction of Tornado speed using AI/ML algorithms. Finally an attempt to create a GUI is shown in Fig.9, but will be fine-tuned in the future.

Models	Average speed m/s	Average speed m/s
W1	2.63	4.85
W2	2.63	3.15
W3	2.28	4.8
W4	2.61	5.2
W5	2.11	5.27
W6	2.68	2.83
Average Speed	2.49	4.35

Table 3

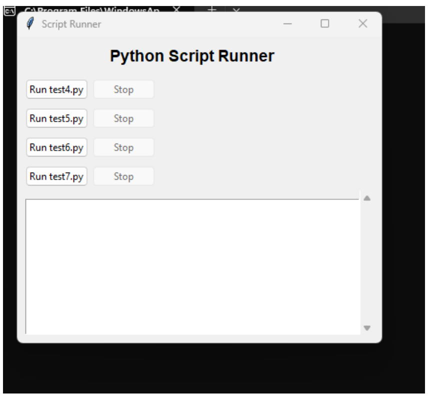


Fig. 9

5. Research Group

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6. Abstract (half page)

Research Theme: AI/ML based Tornado Speed Determination and Prediction from the Windborne Debris Captured in the Tornado, using Video Processing Techniques

Representative Researcher (Affiliation): Sudha Radhika, Associate Professor, Electrical and Electronics Engineering Department, BITS Pilani Hyderabad Campus

Summary: Thus, the object (wind-borne debris) captured inside the moving tornado is tracked and (Assuming this object will essentially have the same rotation speed as the tornado) speed is estimated. The program is coded both in MATLAB and Python and two boundary conditions are considered and the final speed estimation is displayed in Table 3. Usage of the Tornado simulator facility in TPU help to collect a huge video database to fine tune the speed estimation and prediction of Tornado speed using AI/ML algorithms. Finally an attempt to create a GUI is shown in Fig.9, but will be fine-tuned in the future.

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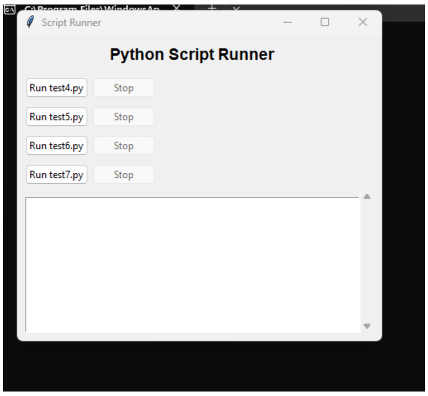

Fig.9

Results - MATLAB