Dynamic Agent-Based Modelling with Data Assimilation in Urban Areas

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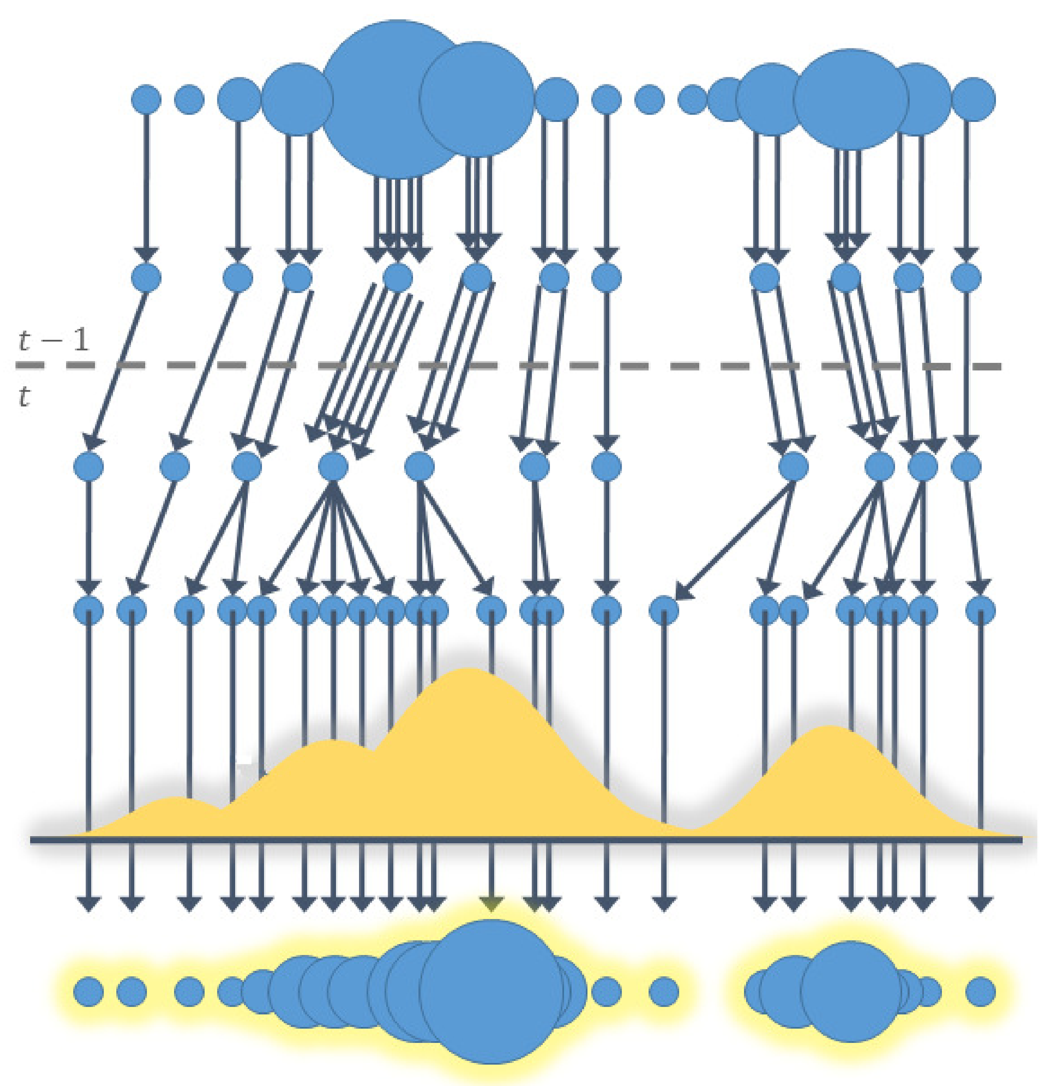
Introduction:

- Standard prediction models are trained on historical data and used to make predictions independently of any new inputs.
- DA models allow for real-time data and other models to be incorporated together to estimate the current state of the system.
- The aim is to take pedestrian movements acquired through a Grand Central Station video feed and produce a DA model using:
  1. Real Time Data
  2. Standard LSTM RNN

Particle Filter Steps:

PFs allow for data assimilation of real-time data and LSTM inputs. Each particle represents a true position of a pedestrian.

1. Place particles uniformly across the train station and assign a weight of 1/N.
2. Randomly move particles.
3. Weight particles according to predictions made by the LSTM RNN model or real-time data every 25-time steps.
4. Make an estimate of the current system state / pedestrian position.
5. Use sequential importance resampling to discard poorly weighted particles and replace with new particles with higher weights.
6. Repeat.



Srinivasan, S. (2019, August 14). *Particle Filter: A hero in the world of Non-Linearity and Non-Gaussian*. Medium. https://towardsdatascience.com/particle-filter-a-hero-in-the-world-of-non-linearity-and-non-gaussian-6d8947f4a3dc

Objective:

The objective of this research was to predict pedestrian movements throughout the Grand Central Train Station through:

- Creating a **Long short-term memory (LSTM)** artificial recurrent neural network (RNN) that predicts pedestrian angle and movement speed based on 5 previous frames of video data.
- Use a **particle filter (PF)** to incorporate LSTM inputs and real-time data to make predictions of pedestrian movements and the gate at which they will exit the train station.
- Compare the performance of the **data assimilation (DA)** model using PF + LSTM to using a LSTM only model and a random walk model.

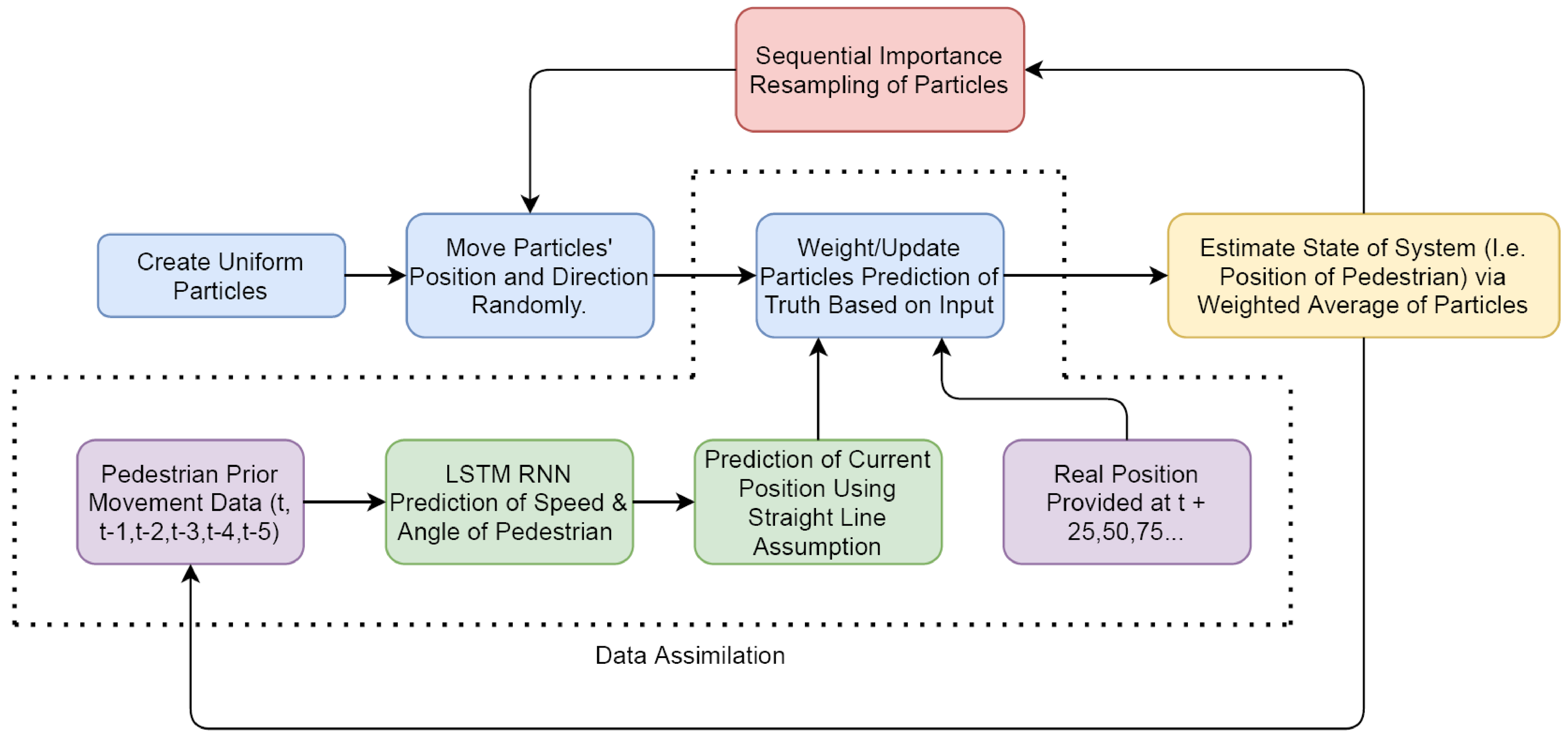


Figure 1: DA Model using PF +LSTM

Visualization of Data Assimilation Model:

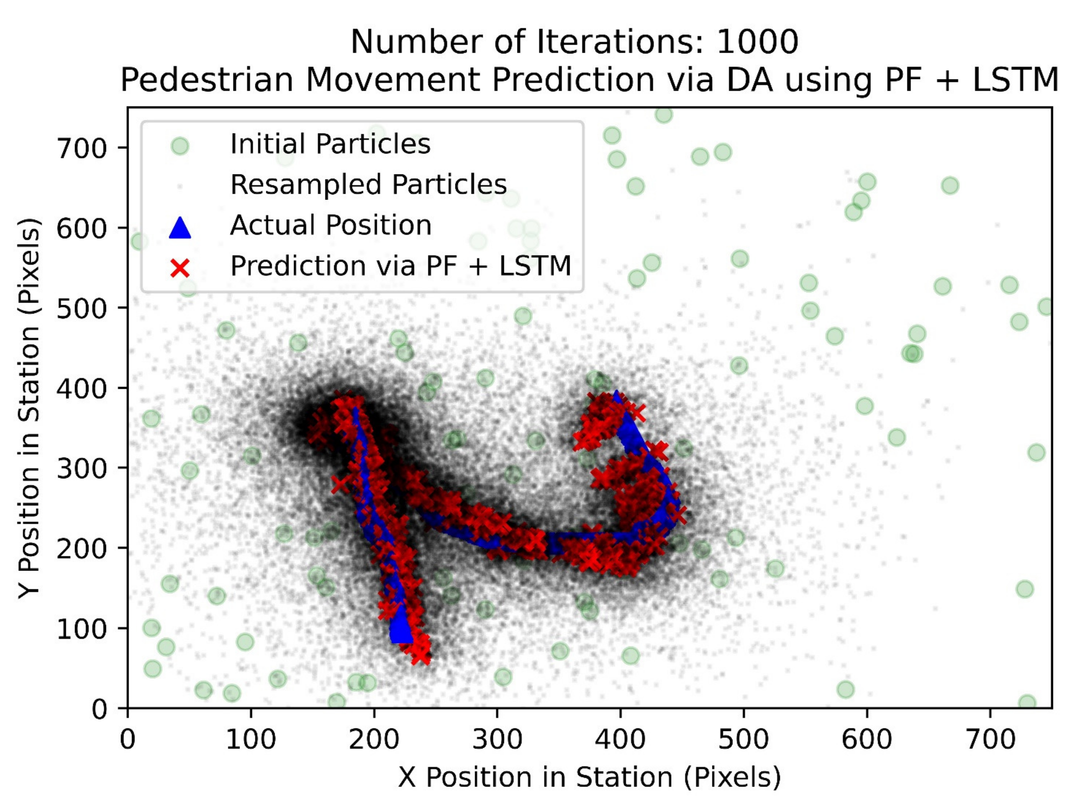


Figure 2: Prediction of Complex Pedestrian Movement via DA using PF + LSTM. (Inputs: N = 100, PedID = 208, GateID = Unknown).

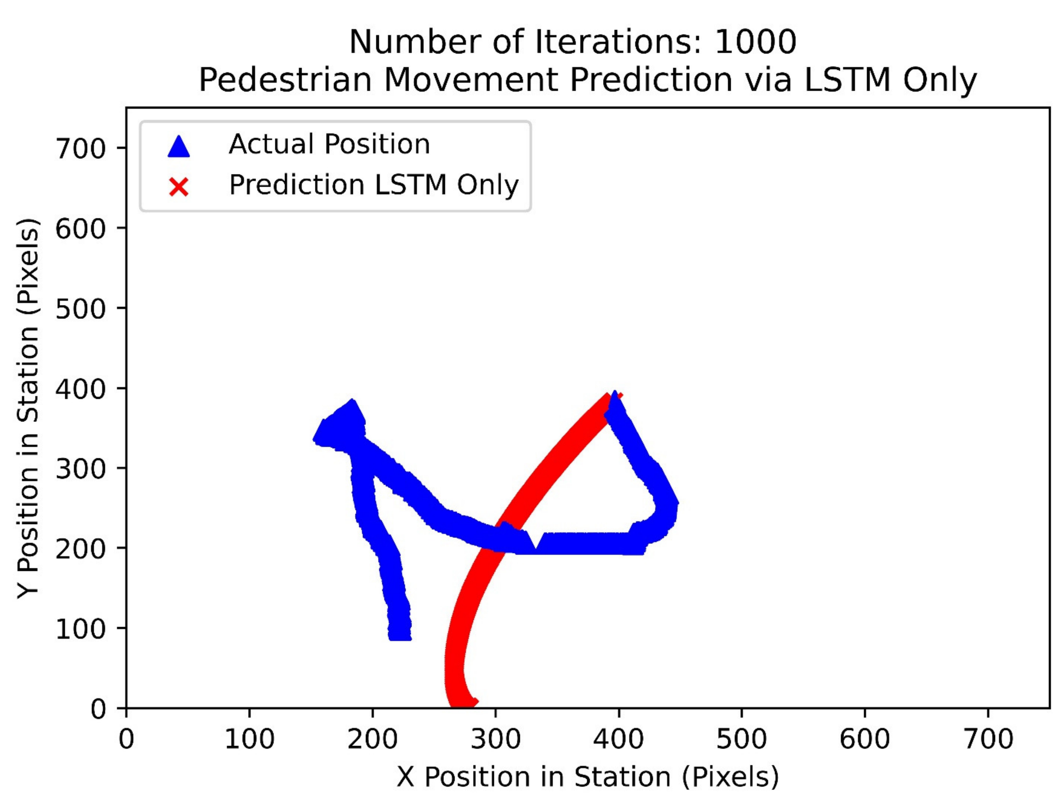


Figure 3: Prediction of Complex Pedestrian Movement via LSTM Inputs Only. (Inputs: PedID = 208, GateID = 9)

Benchmarking:

The DA model using PF + LSTM Input produced in this research was benchmarked against:

1. A model employing only LSTM inputs of speed and angle to predict pedestrian movements using a straight line assumption.
2. A model which randomly sampled speed and angle from a gaussian distribution to predict pedestrian movements.
3. DA Model using PF + randomly sampled speed and angle from a gaussian distribution.

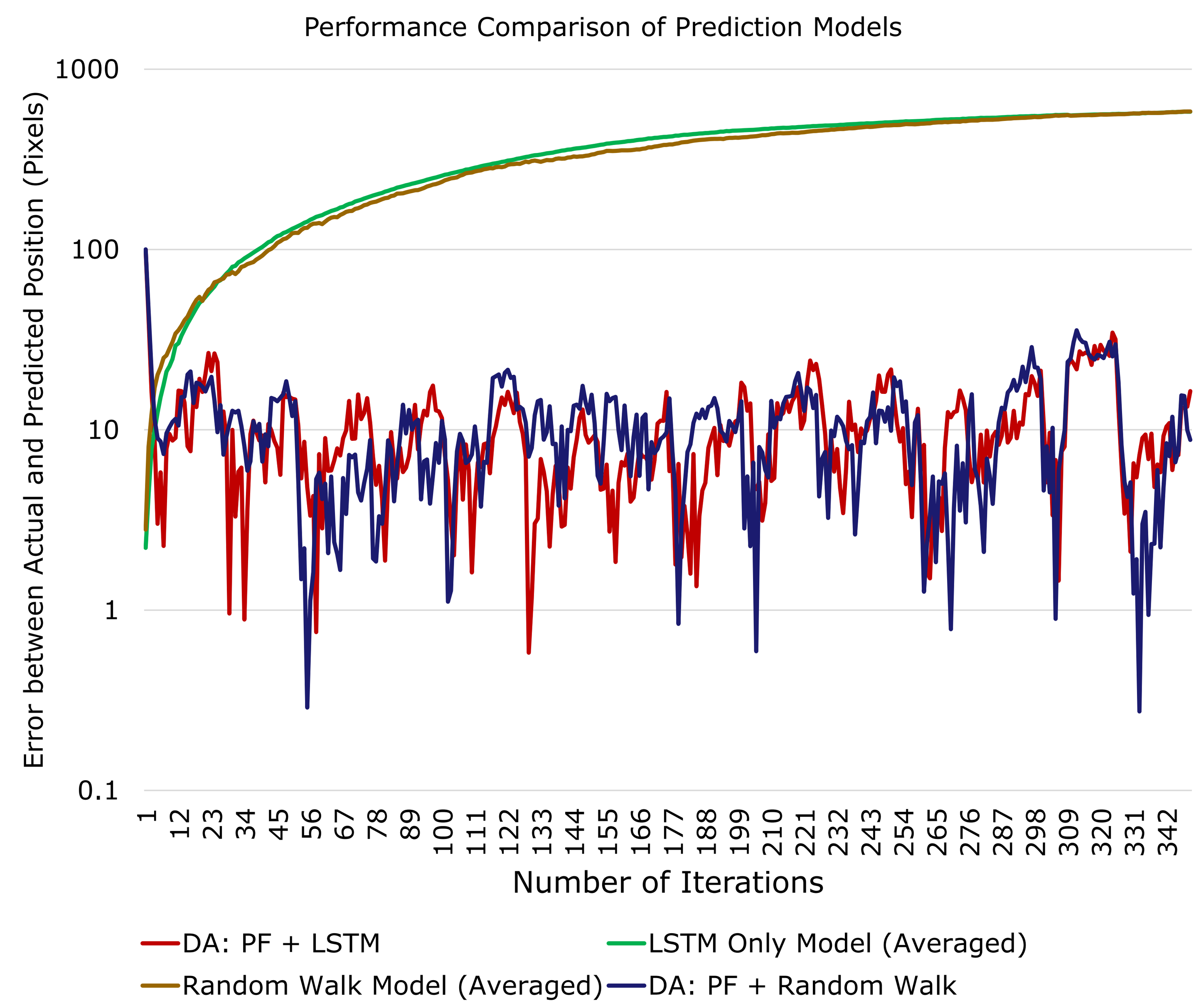


Figure 4: Benchmark of Predictive Models

Conclusions:

- The DA models are able to continuously re-calibrate and hence do not suffer increasing uncertainty unlike the other models.
- The DA Models are able to estimate the gate pedestrians will exit as particle filtering allows for those particles which do not correlate to the true system state to be eliminated upon resampling.
- The other models produce 11 possible pathways.
- Benchmarking showed DA models had an average error about 10 pixels per iteration which was significantly better than the LSTM only and random walk models which had an average error of 367 and 351 pixels per iteration respectively.

See Code and Visualisations:

https://github.com/raylaxmidas/2020-2021-Summer-Research
(See QR Code)