Dynamic Agent-Based Modelling with Data Assimilation in Urban Areas

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Introduction:

Typically, prediction models are trained based on previous historical data and then used to make predictions independently of any new inputs such as real data or other estimation models running simultaneously. DA is a method used in fields such as weather forecasting, which allows for real-time data and information from different models to be incorporated together to estimate the current state of the system. DA models are continuously recalibrated hence do not suffer increasing uncertainty overtime, unlike typical stochastic models.

This research aims to take pedestrian movements acquired through a Grand Central Station video feed and produce a model to predict future motion. This model will use data assimilation of both real-time data and a standard trained LSTM RNN developed in collaboration with Dr Minh Kieu.

Particle Filters:

Particle filtering is a technique that allows for data assimilation of real-time data and LSTM inputs. A particle filter uses particles each with an assigned location and direction, which represent the true position of a pedestrian in the train station. Each particle also has a weight, which is the probability that it represents the pedestrian's true location.

Initially, these particles are places uniformly across the train station and assigned a weight of 1/N, where N is the number of particles. The particle filter updates the belief of the system by randomly moving each of particle.

Next, the particle filter receives a measurement. In this case, a prediction of a pedestrian's future location via an LSTM RNN model returns an estimated speed and angle of the pedestrian. Each 25-time steps, the model also receives the pedestrian's actual position in the train station. Weights are assigned to each particle based on these measurements.

An estimate of the pedestrian's location is made using a weighted average of the particles. Then particles with low probabilities are discarded and replaced with new particles with higher probabilities in a process called sequential importance resampling.

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 **data assimilation (DA)** model using PF + LSTM + Real Data to using a LSTM only model and a random walk model.

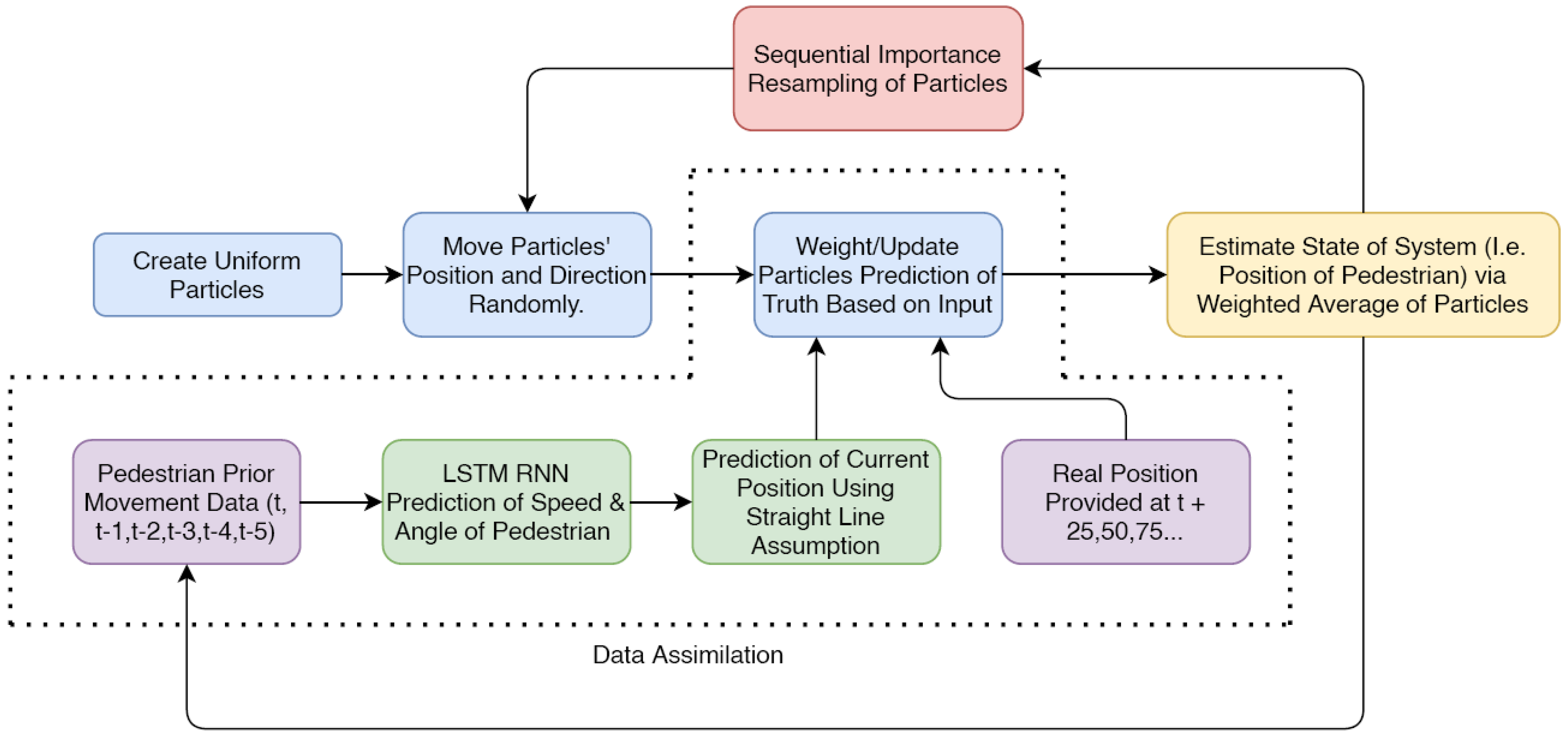


Figure 1: DA Model using PF +LSTM + Real Data

Visualization of Data Assimilation Model:

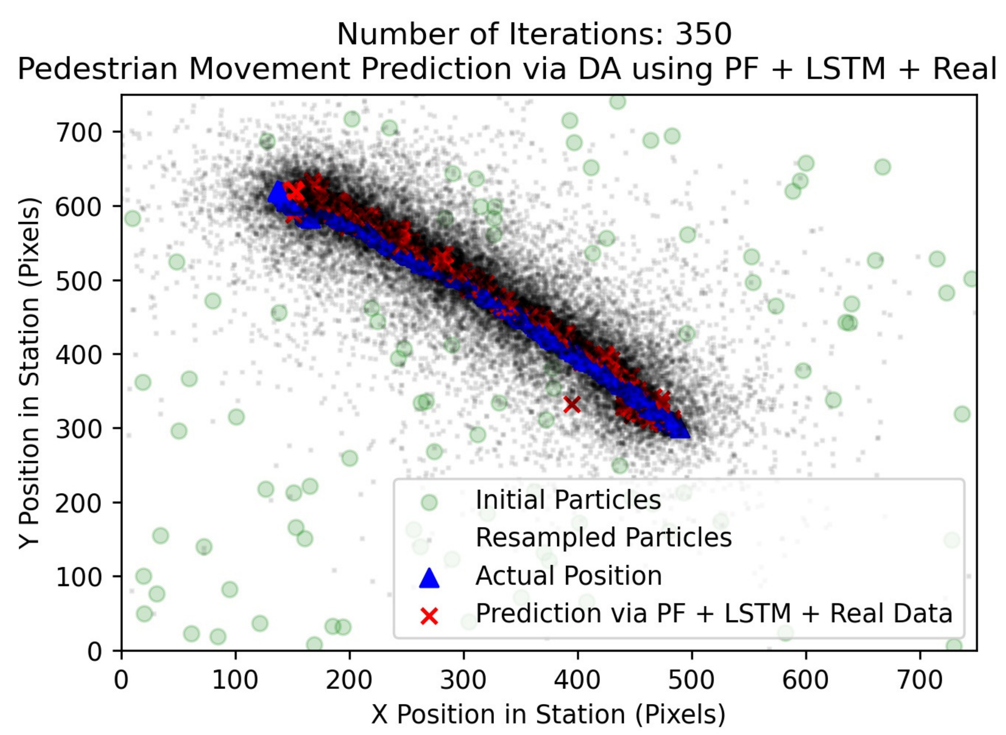


Figure 2: Prediction of Pedestrian Movement via DA using PF + LSTM + Real Data. (Inputs: N = 100, PedID = 7, GateID = Unknown)

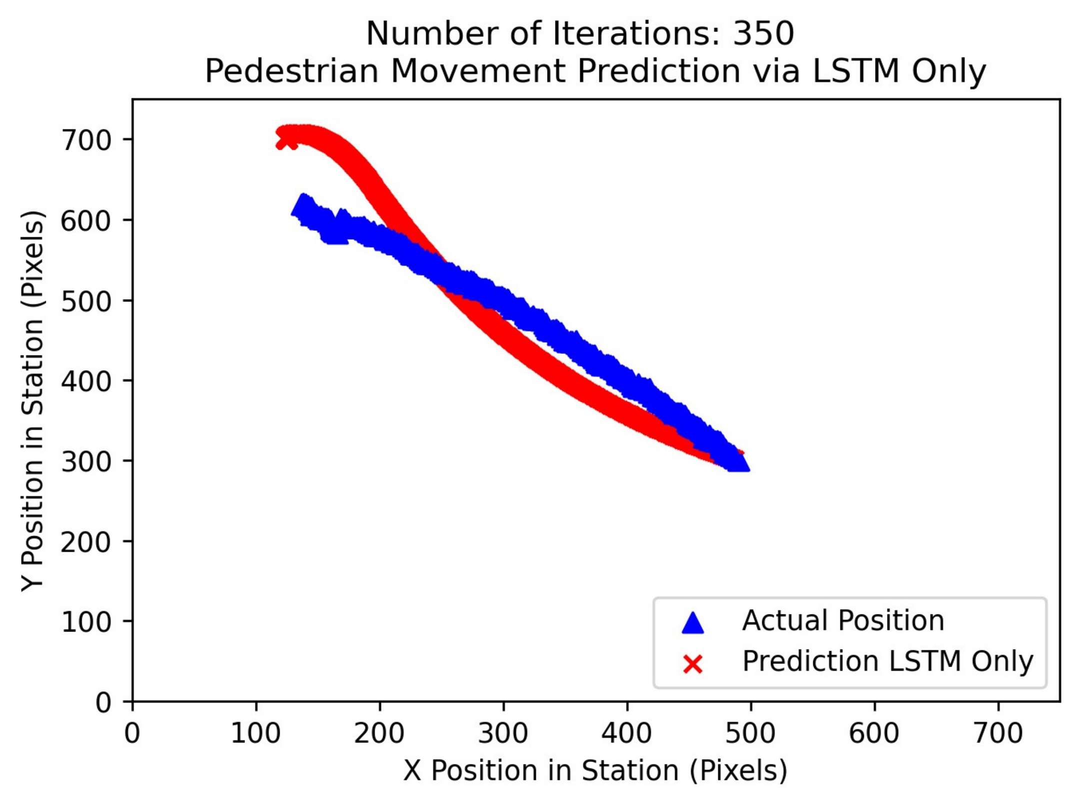


Figure 3: Prediction of Pedestrian Movement via LSTM Inputs Only. (Inputs: PedID = 7, GateID = Known)

Benchmarking:

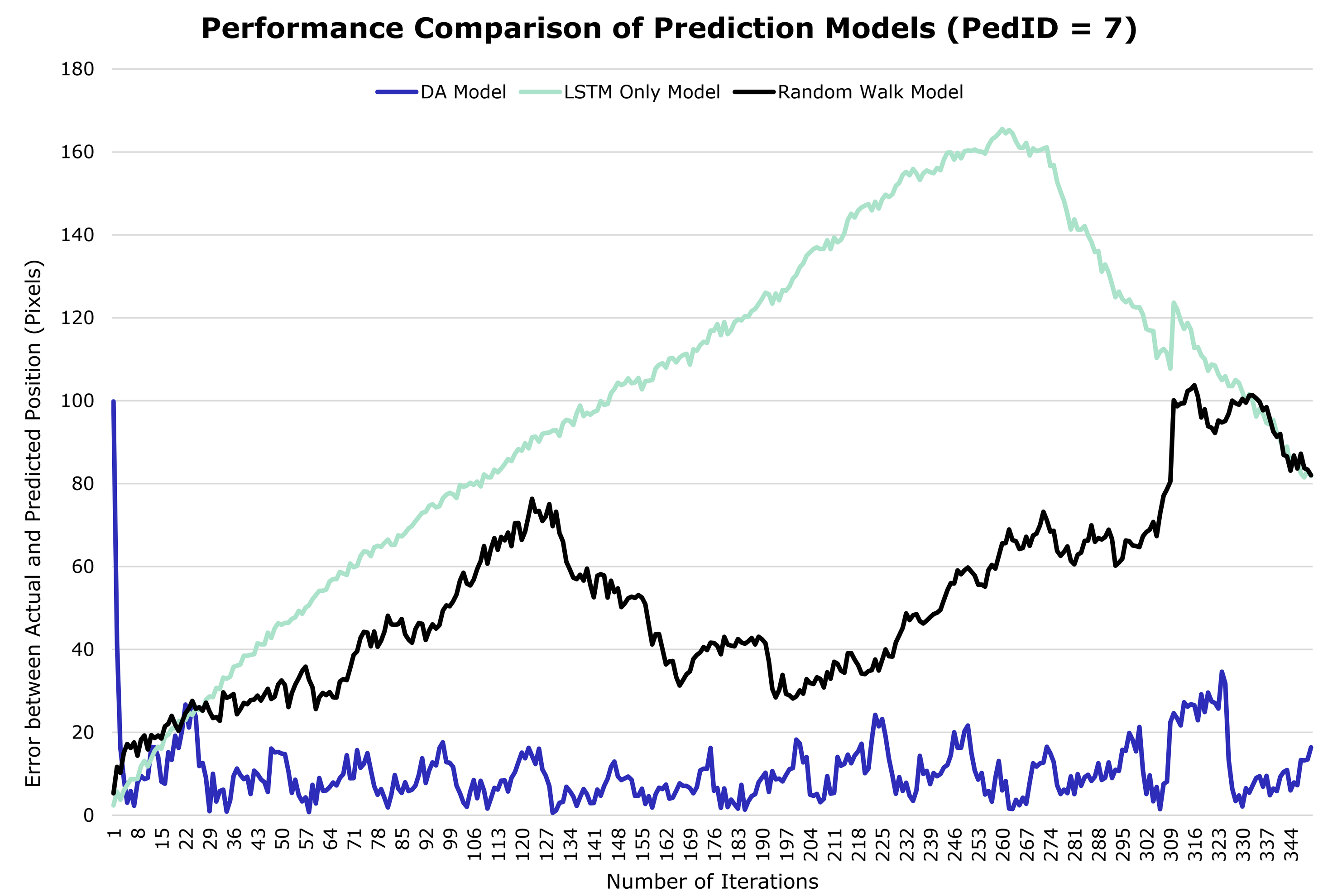
The DA model produced in this research was benchmarked against:

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

It is important to note that each of these models produces ten possible predicted trajectories for pedestrians, one for each possible exit gate in the train station.

The DA model, on the other hand, is able to estimate the gate pedestrians will exit from as particles which do not correlate well to the actual position data provided are eliminated in resampling.

Hence for benchmarking purposes, the LSTM only model and random walk model were provided with the expected exit gate. The error of actual position vs. predicted position in pixels was used to compare the models.



The DA model had an average error of 10.3 pixels per iteration which was significantly better than the LSTM only, and random walk models, which had an average error of 99.1 and 51.7 pixels per iteration.

Link to Code and Additional Visualisations:

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

References:

Malleson, N., Minors, K., Kieu, L.-M., Ward, J. A., West, A., & Heppenstall, A. (2020). Simulating Crowds in Real Time with Agent-Based Modelling and a Particle Filter. *Journal of Artificial Societies and Social Simulation, 23*(3), 3.

Rlabbe/Kalman-and-Bayesian-Filters-in-Python. (n.d.). GitHub. Retrieved February 24, 2021, from https://github.com/rlabbe/Kalman-and-Bayesian-Filters-in-Python