Localisation in WiFi using Novel Deep Architectures

Peizheng Li*†, Han Cui*, Aftab Khan†, Usman Raza†,
Robert Piechocki *, Angela Doufexi*, Tim Farnham†

* University of Bristol
† Toshiba Research Europe Ltd.

Outline

- Introduction
- Experiments
- NN architectures
- Results
- Conclusions

Introduction

Aim: Indoor Localisation based on commodity WiFi equipment.

Type: Active localisation.

Media: Channel state information (CSI) from standard channel sounding.

Scheme: Neural network, supervised learning

Difficulties: Feature extraction and network architectures under complex multipath effect.

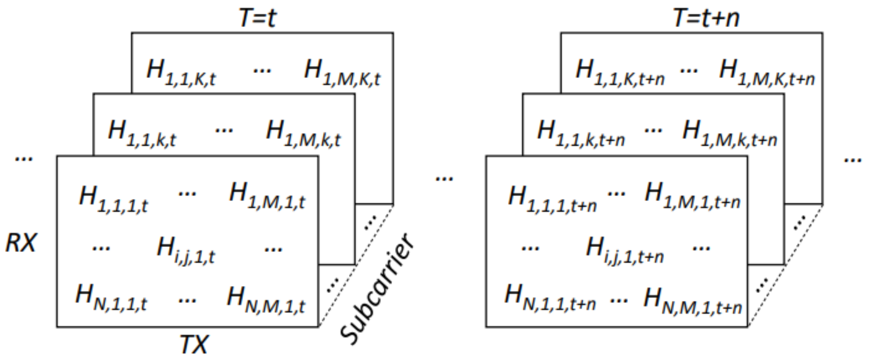

Figure 1: Indication of CSI tuples within a transmission time frame

University of BRISTOL

TOSHIBA

Experiments

Experimental area: Indoor office (6.5m * 2.5m)

CSI rate: 500Hz

Label collection: Opti-track system composed of cameras

Access point: 3

Target tag: curvilinear motions

Dataset: is collected when the target object was carried by a walking human subject to mimic a severe shadowing environment and was continuously moved around in the test area.

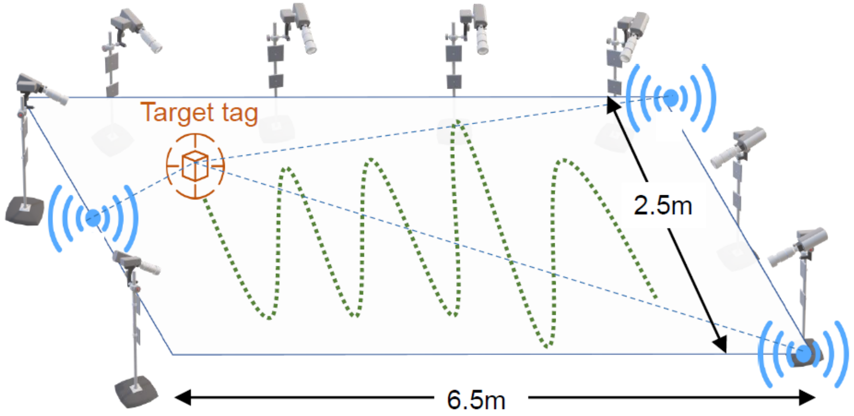

Figure 2: Experiment setup

Figure 3: Real office environment

NN architectures

1. Shallow neural network (SNN)

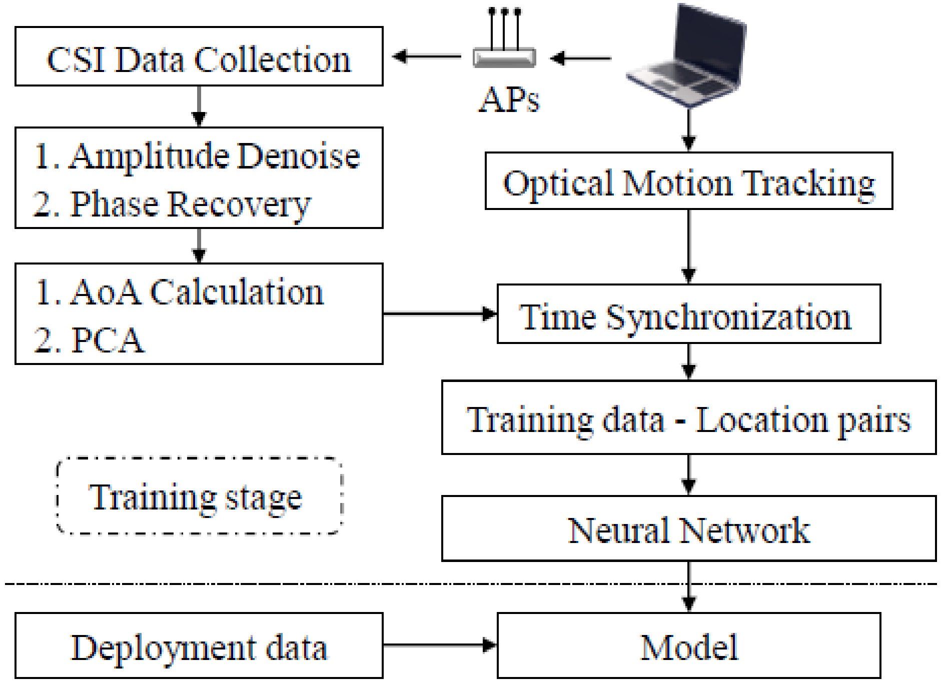

Figure 4: Process diagram of signal processing and training

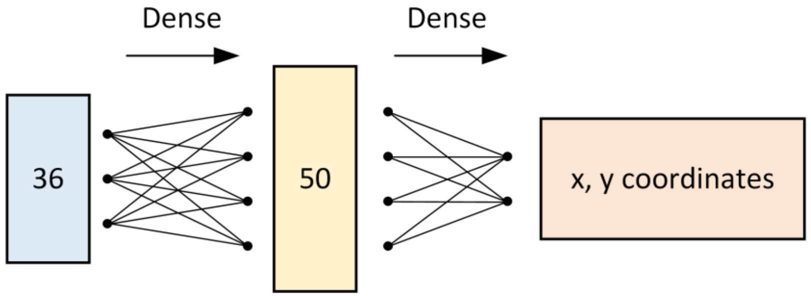

Figure 5: Neural network architecture of SNN

NN architectures

2. Convolutional neural network (CNN)

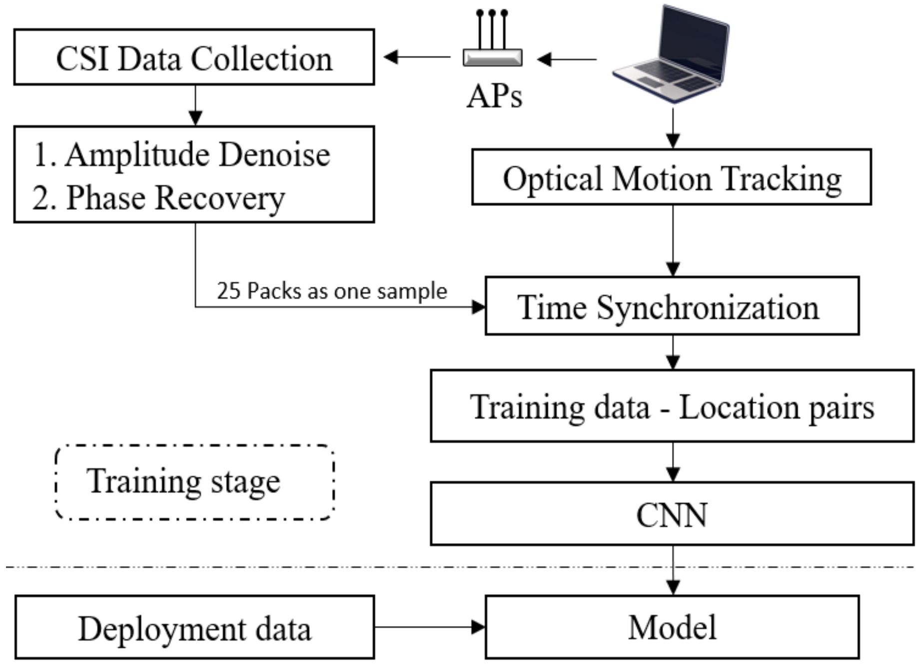

Figure 6: Process diagram of signal processing and training

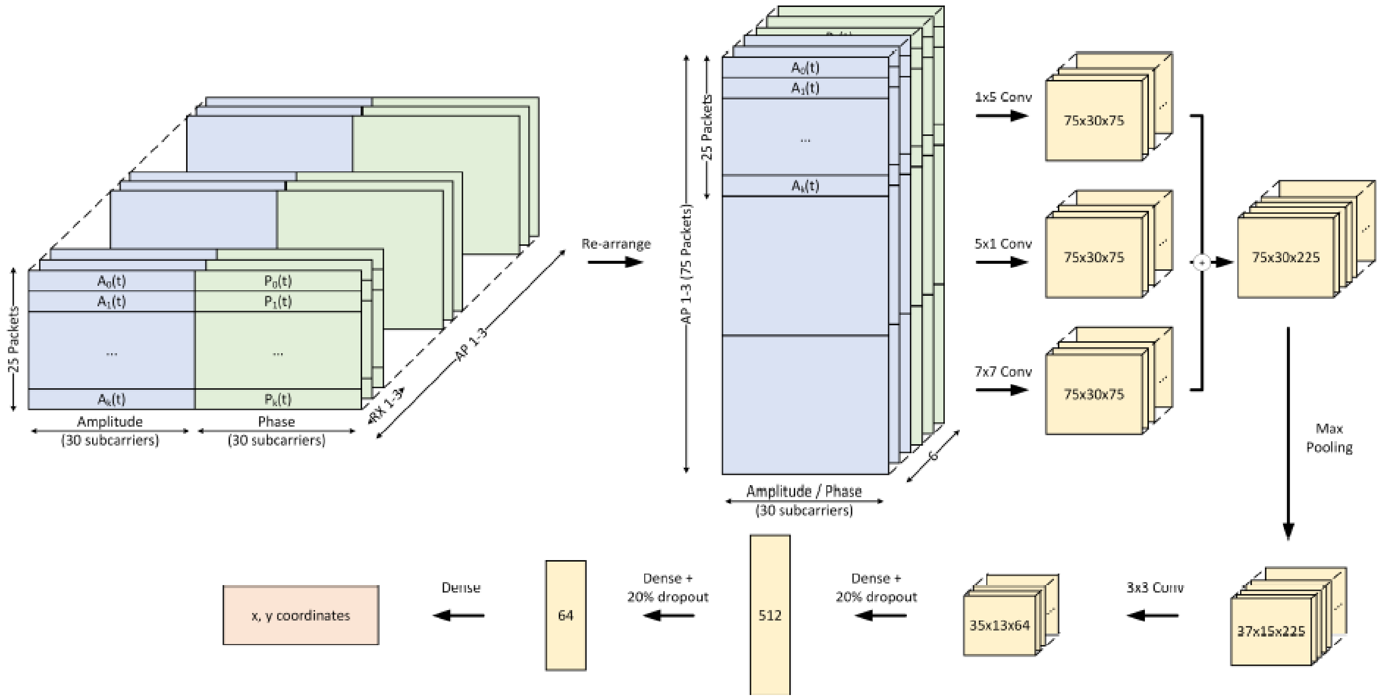

Figure 7: Neural network architecture of CNN

NN architectures

3. Long-short term memory (LSTM)

Data processing is same as in CNN.

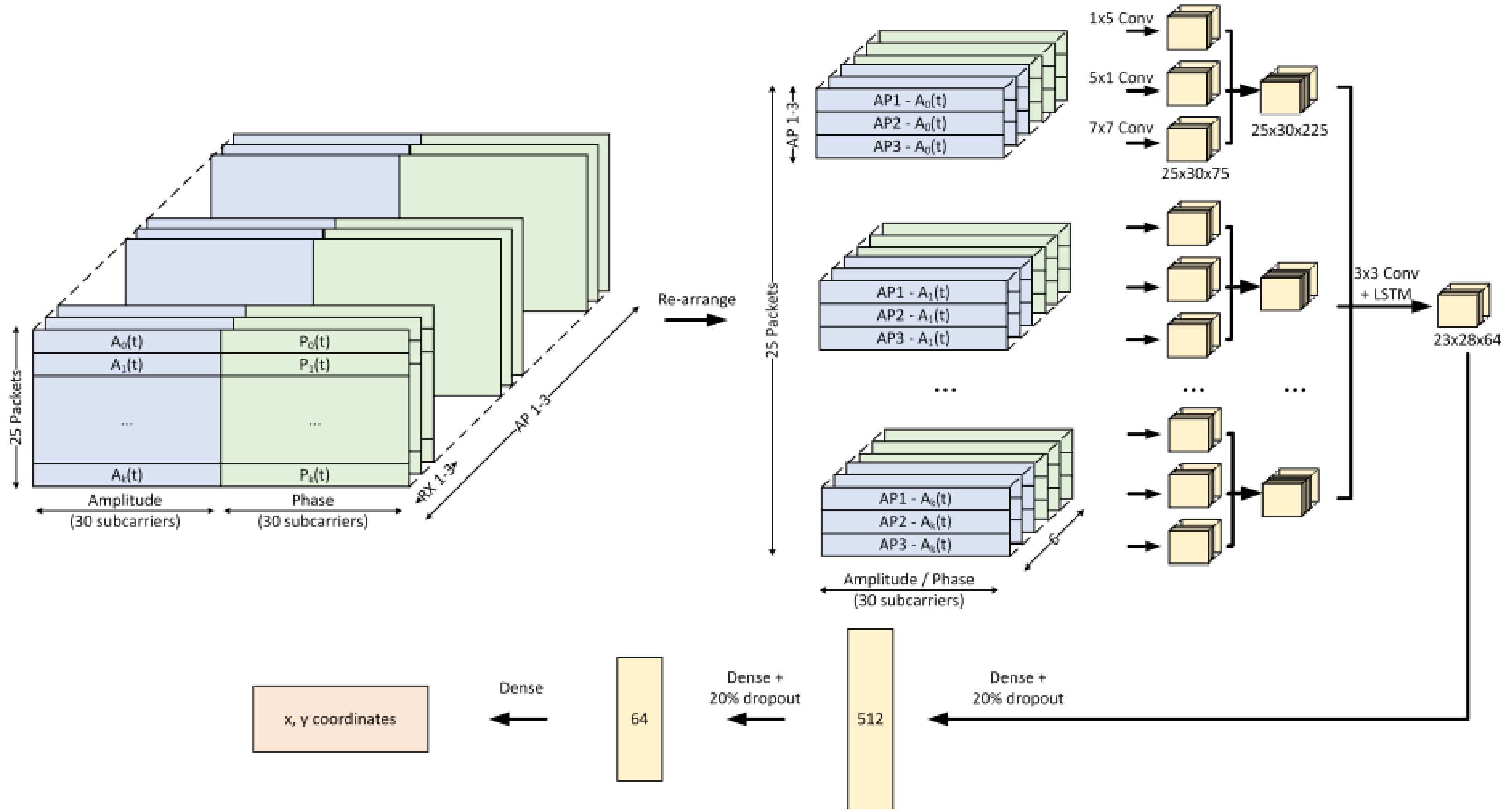

Figure 8: Neural network architecture of LSTM

1. Performance Evaluation

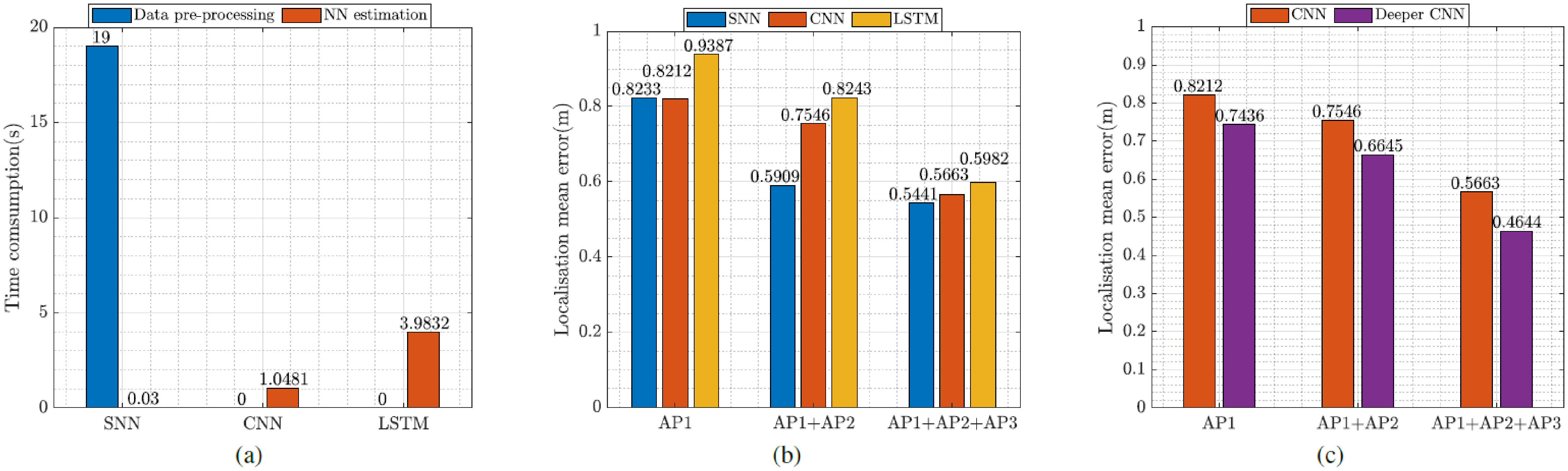

Figure 9: (a) Inference time comparison (1000 samples); (b) Accuracy comparison between the SNN, CNN and LSTM models under different AP combinations; (c) Accuracy comparison between the two CNN models under different AP combinations

Table 1: Comparison of Localisation mean errors for different methods (cross-validation)

	Farnham [20]	SNN	CNN	LSTM
Mean(m)	0.75	0.5441	0.5663	0.5982

University of BRISTOL

TOSHIBA

Results

2. Special Use-case: Non-Constant Velocity Scenario

The motion characteristics contained a pattern sequence of linear-fast, stationary and linear-slow for two minutes.

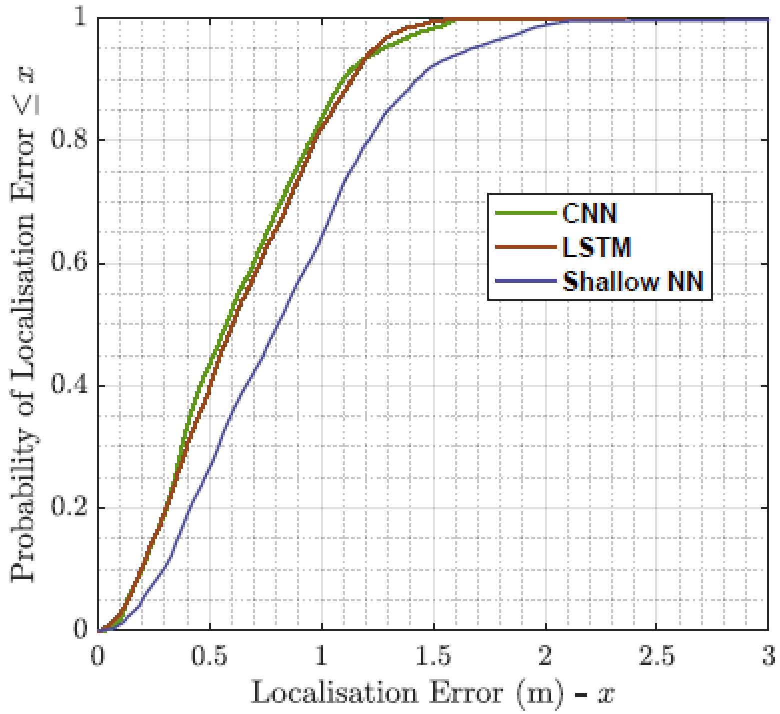

Figure 10: The localisation error CDF of the NN models in the special scenario. The LSTM model is similar to the CNN in accuracy and better than the SNN

Table 2: Localisation mean errors in the special movement scenarios

	SNN	CNN	LSTM
Mean error (m)	0.8559	0.6266	0.6421

Results

3. Data Arrangement Ablation Study

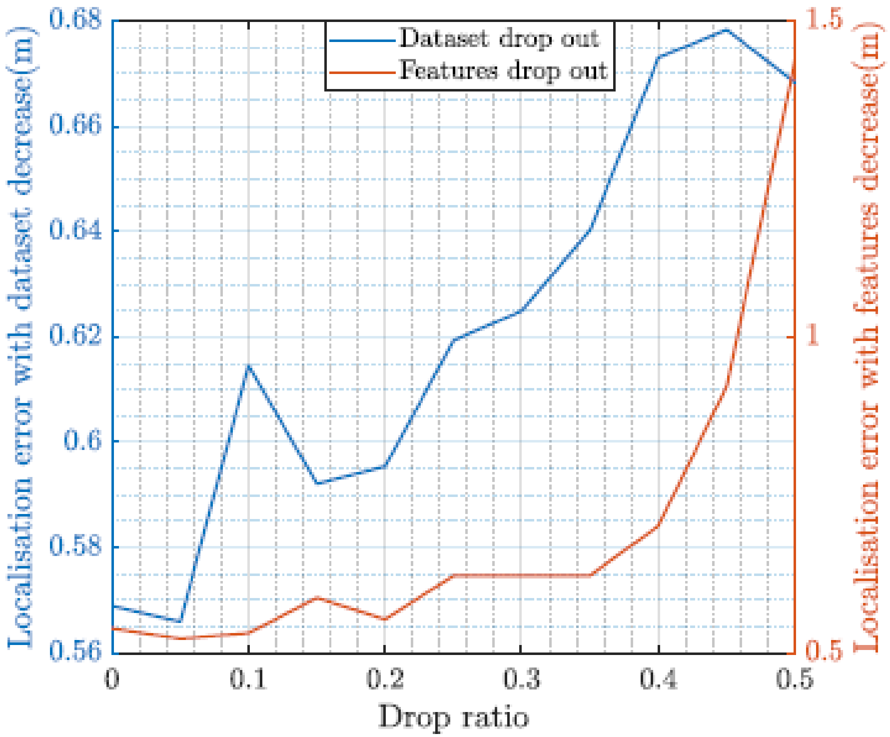

Figure 11: Ablation study for various training data (blue) and feature (red) sizes

Table 3: Features cropping ratio and network parameters relationship

Cropping Ratio	0	0.1	0.2	0.3	0.4	0.5
Network Params	100%	97.38%	94.77%	89.54%	86.92%	84.31%

Conclusions

- Three feasible models for WiFi indoor localisation.
- The process of handcrafted localisation features extraction in SNN is time consuming.
- CNN and LSTM can realise localisation via CSI raw data directly, but the LSTM does not present extra advantages on increase localisation accuracy.
- In a nonconstant speed motion, the CNN shows better generalisation ability.

References

Thanks for your listening