Neural Network-based Indoor Tag-less Localization Using Capacitive Sensors

Osama Bin Tariq
osama.bintariq@polito.it
Politecnico di Torino
Turin, Italy

Mihai Teodor Lazarescu
mihai.lazarescu@polito.it
Politecnico di Torino
Turin, Italy

Luciano Lavagno
luciano.lavagno@polito.it
Politecnico di Torino
Turin, Italy

ABSTRACT

Many applications aim to make smarter the indoor environments where most people spend much of their time (home, office, transportation, public spaces), but they need long-term low-cost human sensing and monitoring capabilities. Small capacitive sensors match well most requirements, like privacy, power, cost, and unobtrusiveness, and, importantly, they do not rely on wearables or specific human interactions. However, long-range capacitive sensors often need advanced data processing to increase their performance. Our ongoing research experimental results show that four 16 cm × 16 cm capacitive sensors deployed in a 3 m × 3 m room can tag-lessly track the movement of a person with a root mean square error as low as 26 cm. Our system uses a median and low-pass filter for sensor signal conditioning before an autoregressive neural network that we trained to infer the location of the person in the room.

CCS CONCEPTS

• **Human-centered computing → Ambient intelligence**.

KEYWORDS

indoor localization; capacitive sensing; neural networks; tag-less indoor localization

1 INTRODUCTION

Indoor environments where most people spend much of their time (home, office, transportation, public spaces) are rarely aware of the presence, activities, or needs of persons, unless the persons actively interact with the environment through switches, knobs, etc.

Most current indoor person sensing solutions rely on devices or tags that are carried by people to become visible to the localization system [13]. But most recent applications that aim to make smarter or intelligent indoor environments would benefit significantly if they can sense person presence and activities in any conditions, even if they do not wear specific tags or devices, nor actively interact with the system through physical or voice commands and controls. Most applications also require unobtrusive sensors (e.g., that can be installed behind room objects, without a direct line of sight), which do not rise privacy concerns (unlike image-based sensors, even when are using blurred visible or infrared imagery), with low equipment and deployment cost, and with reduced maintenance needs (e.g., low energy consumption to extend battery duration or to make possible wireless supply).

Capacitive sensing of conductive and dielectric properties of human body can be used for indoor person sensing [2, 3], identification [4, 6], and localization [1, 5, 7, 9]. They can be small, can be concealed behind non-conductive objects, can consume few energy, do not raise privacy concerns, and can be easy to install and maintain.

Yet, the capacitive sensors' strongly-nonlinear distance-capacitance dependency, as well as their operation close or below noise level (for long-range sensing), require advanced processing techniques to improve the sensor performance [8, 10]. In particular, we present in this work some promising preliminary results of our exploration of sensor signal filtering combinations and machine learning algorithms, such as multilayer perceptron and autoregressive neural networks (NNs) trained on the abstract signatures of movements of a person in our experimental room.

2 MAIN CONTRIBUTIONS

Previously, we showed that long-range capacitive sensors can be used to accurately classify the position of a person among 16 possible locations within a 3 m × 3 m room using specific signal filtering and machine learning processing [9, 12] (see Figure 1).

In this work, we use similar sensors but a modified signal processing chain to track the location of a person that is moving freely within the room. To increase movement tracking accuracy, we increase the sensor data rate from 1 Hz (used previously [9]) to 3 Hz using an improved sensor data discretization and acquisition algorithm (see Figure 2). To decrease noise, the sensor uses higher sampling frequency, 24 Hz, and downsamples it to 3 Hz before transmitting.

Additionally, along the capacitive sensor data, we also acquire the position of the person in the room using an ultrasound-based localization system (shown in Figure 3), which we use as ground truth.

Furthermore, the system can consider now the dynamics of person's movement. For this, we use an autoregressive

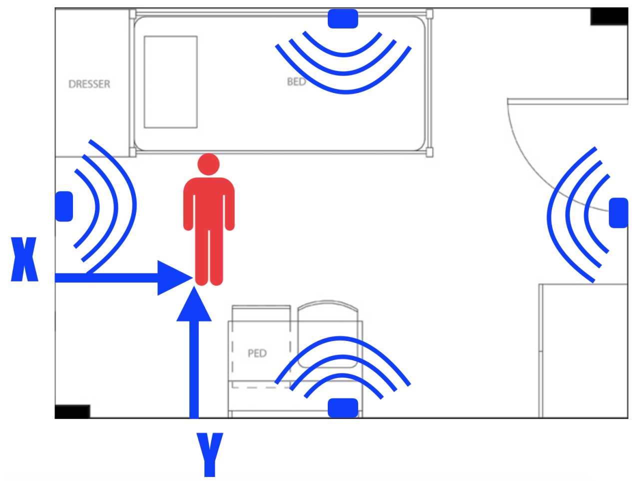

Figure 1: Conceptual layout of room with sensors. Combination of capacitive sensors would be able to estimate coordinates of a person inside room.

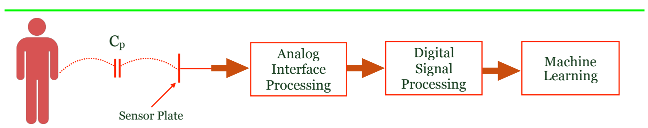

Figure 2: The acquisition and processing chain for capacitive sensor data includes sensor analog data acquisition and digital conversion block, and a digital preprocessing (filtering) block, before entering the neural network block for training or inferring.

neural network to which we provide, for both training and inference, a segment of the person's past trajectory, from which it can characterize the movement in terms of, e.g., speed, direction, or acceleration.

3 METHODOLOGY

Figure 2 shows the experimental workflow, which is:

- collect timestamped capacitive sensor data labelled with accurate room position of the person (ground truth);
- preprocess (filter) the sensor data;
- use filtered data to train, test, and optimize an autoregressive neural network.

As shown in Figure 1 and Figure 3, four 16 cm × 16 cm capacitive sensors are installed in the middle of each room wall, roughly at the height of person chest. The accurate person location is synchronously acquired using a commercial ultrasound-based localization system, with four anchor sensors placed high in the four room corners and the fifth, mobile, attached to the person.

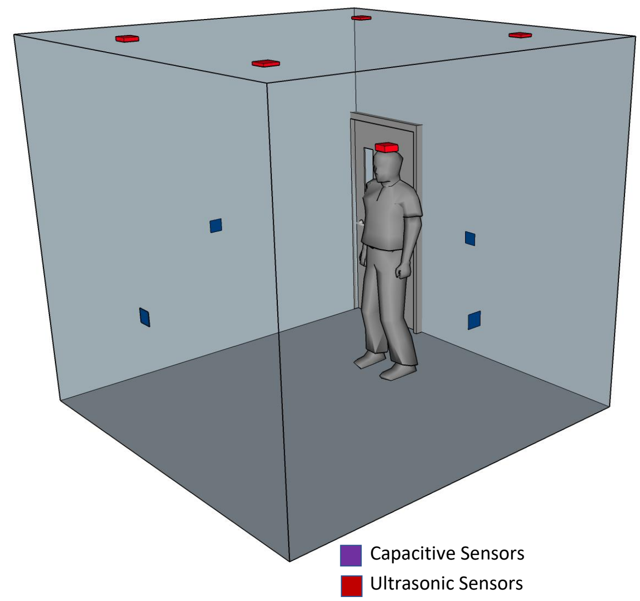

Figure 3: Our 3 m × 3 m experimental room includes one Capacitive sensor on each wall, and five ultrasonic sensors which provide the ground truth (four ultrasonic sensors are on ceiling and one is carried by the monitored person.

We preprocess the acquired capacitive sensor data using a wide-window median filter to reduce sensor drift, followed by a low-pass filter to remove high-frequency noise.

In these preliminary experiments, we used a fixed architecture for the NN made of 64 neurons on the first hidden layer, flattened and with 50% dropout, 32 neurons in the second hidden layer, with 30% dropout, 8 neurons the last hidden layer, and 2 neurons in the output layer (which output the X and Y co-ordinates of the person in the room). The NN was implemented using Python library Keras using the Tensorflow back-end. For NN training and optimization, we split the data in three sets: 60% for training, 20% for validation, and 20% for testing.

Top plot in Figure 4 shows the normalized output of one sensor after preprocessing for long-term drift and noise removal. We use frequency measurement as proxy for sensor capacitance, which is roughly proportional to $1/d$[2, 3], where d is the distance between the sensor and person and is shown in the bottom plot. Due to the strong non-linear dependence between sensor output and the distance to person, we can see strong sensor output variations when the person is close to it, and flattened readings otherwise, close to noise level. The strong non-linear sensor response increases the complexity of accurate inference of person position.

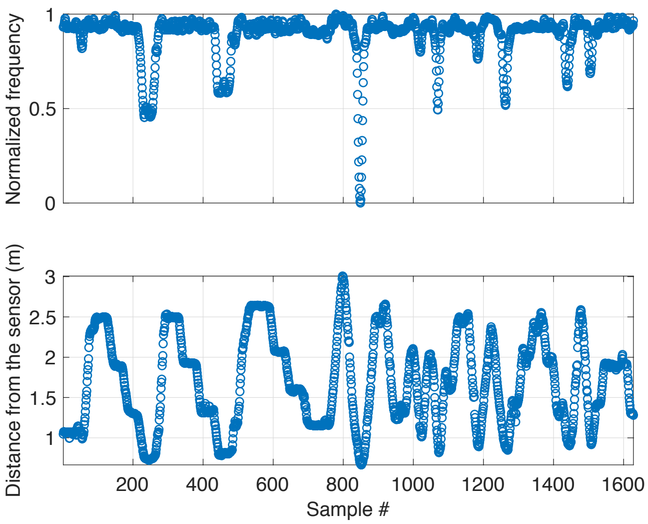

Figure 4: Sensor output after filtering (top) and the distance of a person from the sensor as the person moves around the room (below).

4 ANALYSIS AND RESULTS

To optimize the tracking accuracy of person movements in the room, we used GNU parallel [11] to explore the effects of several design parameters (DSE) of the processing flow shown in Figure 2 as follows:

NN Input Window (NN-IW) which is the length, in seconds, of the sliding segment (window) of the person's past trajectory that we provide in input to the NN. DSE values of NN-IW: 2 s, 5 s, 10 s, 12 s, and 15 s. The sliding step is always one sample.

Median Filter Window (MFW) is the length, in seconds, of the sliding window of the median filter that we use to reduce the long-term drift of the sensor data. The drift is typically caused by slow changes of environmental conditions, like electric potential or humidity. DSE values of MFW: 50 s, 100 s, and 150 s.

Interpolation Frequency (IF) which we use to augment the experimental data for NN training. DSE values of IF: 3 Hz (which is the actual experimental data sampling rate), 10 Hz, 20 Hz, and 40 Hz.

Data Split Order which is the order in which we split the experimental data stream in the three sets we use for NN training, validation, and testing. We include in DSE all six permutations.

Table 1 shows the correlation between the best ten root mean square error (RMSE) results of trajectory prediction and the DSE parameters. Minimum RMSE is about 0.26 m. We note that the optimum NN-IW values are around 10–12 s, the best MFW value is 50 s, while experimental data augmentation beyond its original sampling rate of 3 Hz does not seem to significantly improve the accuracy.

Table 1: Effect of several data processing parameters on the root mean square error (RMSE) of person position inference accuracy: input window for the autoregressive neural network (NN-IW), median filter window (MFW), and interpolation frequency (IF).

RMSE (m)	NN-IW (s)	MFW (s)	IF (Hz)
0.263	12	50	3
0.265	10	50	10
0.266	10	50	3
0.274	12	50	10
0.283	10	50	20
0.286	15	50	3
0.288	5	50	40
0.294	15	50	10
0.294	5	150	3
0.296	5	50	10

Figure 5 allows a visual comparison between the inferred X (top plot) and Y (bottom plot) co-ordinates of person position while roaming freely within the room, and the reference X and Y co-ordinates reported by the reference ultrasound-based localization system. They are generally very well correlated, except when the person reaches positions close to any of the 3 m × 3 m room walls.

5 FUTURE WORK

We showed the experimental results of our preliminary exploration of some design parameters of an indoor localization system using capacitive sensors and an autoregressive neural network. The best RMSE accuracy, of 26 cm, is promising.

We singled out several localization accuracy limiting factors on which we will focus next. First, we will try to optimize sensing and processing techniques to reduce sensor strong drift and noise level, since the signal decays fast for long sensing distances (10–20 times the sensor diagonal size). Second, we plan to comparatively analyze the inference accuracy of several NN architectures that can make better use of the dynamics of person movement.

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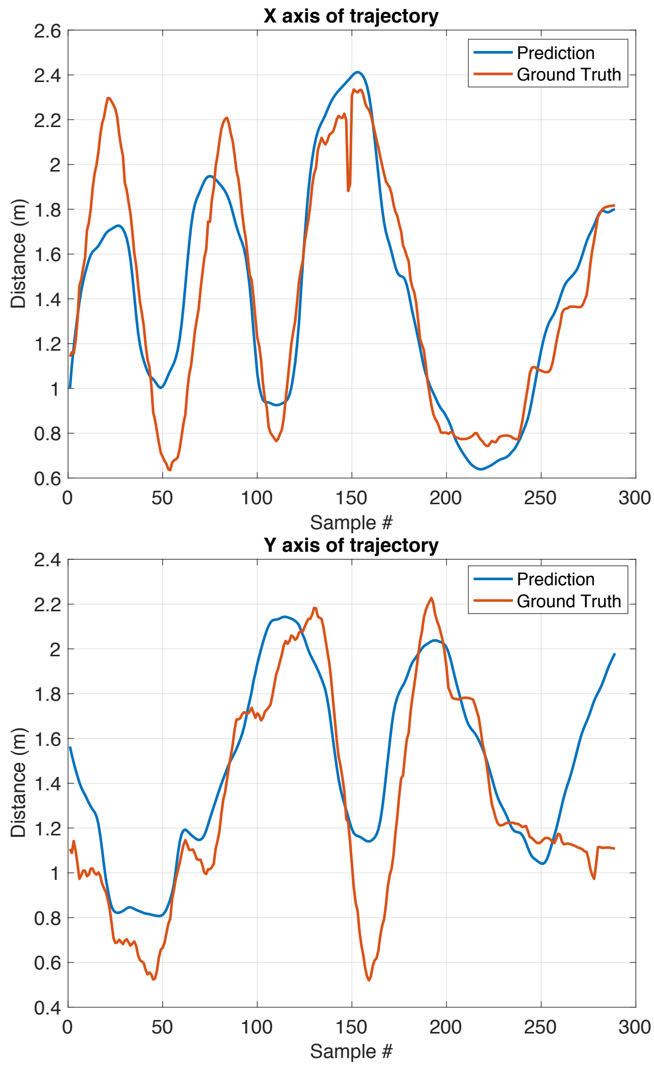

Figure 5: Inferred X (top) and Y (bottom) co-ordinates of person position while moving within the 3 m × 3 m room vs ground truth from the reference ultrasound-based localization system.

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