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Calibrating Recurrent Neural Networks on Smartphone Inertial Sensors for Location Tracking

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***Abstract*—The need for location tracking in many mobile services has given rise to the broad research topic of indoor positioning we see today. However, the majority of proposed systems in this space is based on traditional approaches of signal processing and simple machine learning solutions. In the age of big data, it is imperative to evolve our techniques to learn the complexity of indoor environments directly from data with modern machine learning approaches inspired from deep learning. We model location tracking from smartphone inertial sensor data with recurrent neural networks. Through our broad experimentation we provide an empirical study of the best model configuration, data preprocessing and training process to achieve improved inference accuracy. Our explored solutions are lightweight to run efficiently under limited computing resources available on mobile devices, while also achieving accurate estimations, within 5 meters median error from inertial sensors alone.**

***Index Terms*—deep learning, location tracking, indoor localization, inertial sensors, recurrent neural networks, dead reckoning**

I. Introduction

A growing number of location based services has given rise to the research topic of position estimation, proposing innovative solutions for the more difficult cases, such as for indoors where access to GPS is unreliable. Using the inertial sensors available on smartphones (accelerometer, gyroscope and magnetometer) good position estimations are achievable, although not without limitations.

Inertial sensors are commonly used to construct Dead Reckoning systems, taking a confident observation as starting point, followed by consecutive location estimations on top of previous locations by determining direction of movement and traveled distance [1]. However, a severe problem with this approach is that occasional erroneous estimations (due to sensor noise, drift and device calibration) are cumulative in the system, leading to increasing estimation errors very fast [2]. For this reason, Dead Reckoning is often augmented with opportunistic anchoring to the physical space, either by identifying unique signatures of sensors [3], activity recognition [4], ambient conditions [5], collaborative estimation [1] or by radio signal signatures [6].

Exploring the literature, the vast majority of previous solutions to perform location estimation from inertial sensors proposes heavily engineered approaches. These are as good as the quality of human expert observations and their modelling skills. The problem with this manually engineered approach is that edge cases will always exist that are hard to formulate and integrate in these systems, which is also the reason for the wide performance variation we see between such systems. We argue that manual formulation of the location estimation process is limited and so we should rely on automatic learning directly from data instead, without much human intervention. In this age of data driven systems, adopting modern machine learning techniques, such a deep learning, will help to move our community forward.

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In this work we explore a robust modelling solution, Recurrent Neural Networks (RNN) for the task of position tracking on smartphone inertial sensors. RNNs have proven effective in other sequence based tasks, such as in machine translation, speech, and natural language processing. We explore a range of data preprocessing choices and model configurations to assess their impact on location estimation accuracy by training several different models. We find that data down-sampling is beneficial to having a smaller model that can run on mobile devices, while achieving below 5 meters median error, and time window overlapping helps to strengthen observations in the model while also expanding the available training data to benefit training. Transferring models trained on data from one device to perform estimations on another device is also explored here, showing the good generalization of RNN models.

Although we move the burden of developing localization systems to generating good labeled training sets, we believe this is more scalable since data collection is easier than human intervention to alter previous systems for new environments and edge cases. Solutions based on infrastructure cameras to extract location estimation [7] for sensor data labeling can be one approach to enhance training data collection at scale.

This paper makes the following contributions:

- We formulate location tracking as a recurrent neural network problem, incorporating all the complexity of mobility model generation into an automatic learning process from location labeled sensor data.
- Training and testing of recurrent neural networks is done on a sizable dataset we collect for this exploration.
- We offer insights into the best options to calibrate recurrent neural networks to achieve improvements in location estimation with these recurrent neural network models.

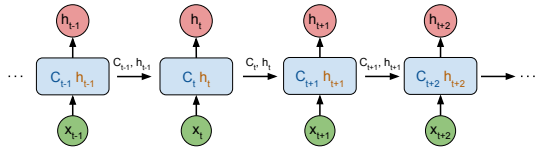


Fig. 1. The structure of a recurrent neural network with LSTM units, which estimates an output h_t based on an input X_t and information received from previous blocks in the chain (C_{t-1} and h_{t-1}).

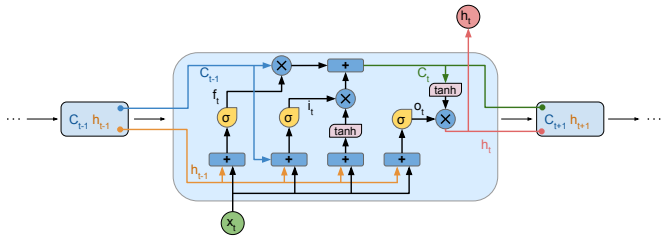


Fig. 2. The flow in one LSTM unit, showing long-term memory accumulation in C_t and short-term term memory representing the output of previous unit h_{t-1}.

II. Methods

This section presents the deep learning technique we adopt to perform indoor localization on smartphone inertial sensor data. We adopt a validated recurrent neural network technique showing good performance in other domains to produce a modern perspective to the classic dead reckoning solution.

A. Dead Reckoning as Recurrent Neural Network

Dead Reckoning is the process of estimating continuous locations by starting from a known point (e.g., by detecting entrances [8]) and estimating consecutive positions based on a stream of observations (direction of movement and displacement). This resembles the process performed by recurrent neural networks, building on previous estimations (or features from previous estimations) and on new environment observations to produce a sequence of predictions. In this section we present the constituent components of a popular recurrent neural network model, Long-Short Term Memory (LSTM); and how this can be applied to the task of position tracking from streaming inertial sensor data.

LSTMs have proven their efficiency on dealing with sequential data in speech recognition and machine translation. These are constructions based on fully-connected layers, passing on information from one prediction stage to the next in a way that mimics memory in human brain [9]. Based on previous estimations and fresh observations from the environment, new estimations are produced in sequence with previous estimations and receptive to streaming observations. The chain of estimations is presented in Figure 1, where C_t is the long-term memory at time t and h_t is the block output at time t, or short-term memory, both passed on to the following LSTM block in the chain.

The vanishing gradient problem in RNNs is solved by LSTMs through the long-term memory. However, this long-term memory cannot accumulate indefinitely, so a forget gate is used to keep the size tractable. Figure 2 shows the internal structure of one LSTM unit. In each unit, there are not only input and output gates but also a forget gate that controls the amount of information propagated to the next block and what is dropped in the current stage [10]. The input to a block for us is a concatenation of acceleration, gyroscope and magnetometer values over a time window.

The value in the current state is controlled by the forget gate f signal. Specifically, this saves the value when the signal is set to *1* and forgets when the gate is set to *0*. The activation of receiving a new input and propagating this are determined by signals to the input gate and to the output gate respectively [11]. Equations 1 to 6 show the formulation of transformations performed inside the block, where W are weights learnt in training.

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1}) \quad (1)$$
$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1}) \quad (2)$$
$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1}) \quad (3)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot h(W_{cx}x_t + W_{cm}m_{t-1}) \quad (4)$$
$$m_t = o_t \odot c_t \quad (5)$$
$$p_{t+1} = \text{Softmax}(m_t) \quad (6)$$

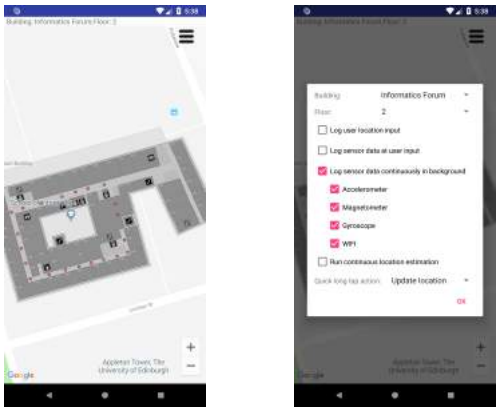
As inertial sensor data is streamed in time sequences, the LSTM model is ideal for location estimations on this type of data. The size of one sample is $time\_step * no\_features$, where features are the magnitude of measured values on the three axes of each sensor, accelerometer, gyroscope and magnetic sensor. A time window is formed of a number of sensor signal samples collected over such interval of time and regularised to a fixed sampling rate. Each data instance has a target position (X_i, Y_i) as label. On this data representation, the LSTM model produces position estimations in coordinates (X_{est}, Y_{est}). This is formulated by equations 7–9.

$$x_{-1} = \text{Sensor Data}(I) \quad (7)$$
$$x_t = W_e S_t, \quad t \in \{0...N-1\} \quad (8)$$
$$p_{t+1} = \text{LSTM}(x_t), \quad t \in \{0...N-1\} \quad (9)$$

Because LSTMs use long-term memory, this has an advantage over traditional Dead Reckoning in tolerating more local noise, benefiting from long-term memory as an superimposed global filter. Also, long-term memory is important to avoid vanishing gradients when propagating information over longer sequences. Through this, distant events like unique signatures on the path [3] and specific activities [4] are used as anchor points automatically in the model, specializing on the most distinctive observations and their order in training sequences.

III. Evaluation

This section presents our data collection process, model training and validation of different data preprocessing options and LSTM configurations.



(a) Ground truth input interface

(b) Sensors data collection configuration

Fig. 3. Screenshots from our Android application used to collect sensor data.

A. Data Collection

Sensor data is collected with an Android application designed and built specifically for this task. This application can be configured to collect inertial sensor data (accelerometer, magnetometer, gyroscope) continuously in foreground benefiting from a visual interface to accept user inputs, or in background mode when carrying the phone in pocket with the screen off. Ground truth information is provided through the visual interface displaying the building map by user inputs in the foreground mode (as shown in Figure 3(a)). A long tap on the map triggers an event to store the latitude and longitude coordinates as provided by Google Maps API at the location indicated by the user as ground truth coordinates. This application can be configured to operate in tandem with a second phone operating in background mode to collect inertial sensor data only (Figure 3(b) shows the options available to configure the application for data collection in background mode). This permits the second phone to be placed in any position, in a bag, in pocket or anywhere else without the need for user interactions with the device during data collection, which resembles the perspective of sensors in natural motion.

Ground truth labels are transferred from the phone operating in foreground mode and accepting manual location inputs from our human annotator to the phone operating in background mode, which collects sensor data. We conducted a long data collection campaign following this collection approach. Ground truth positions were provided sporadically by an external observer, by following participants on the experiment track, to input ground truth locations with the foreground phone. To avoid calibration across many participants due to variations in walking styles [4], we collected data from a single participant who performed 14 runs on the same trajectory, each taking different amount of time exercised by the speed of walking, between 2.5 minutes to 4 minutes for one run. This variation in walking speed was enforced as a stringent condition to experiment the ability of LSTM models to differentiate between various walking conditions.

B. Data Preprocessing

The Android API provides sensor samples on event basis, updating only on value change, which leads to irregular sampling frequency. We normalise the input frequency by interpolating at a rate of 1 kHz. These are grouped in a time window, which we discussed later, and associated one position (latitude, longitude) to each time window by interpolating available ground truth locations (which are already dense enough, about 0.5 Hz).

We also impose a position invariant condition by working with the magnitude value on the three orthogonal axes of measurement:

$$sensor_{magnitude} = \sqrt{sensor_x^2 + sensor_y^2 + sensor_z^2}$$

where sensor_$\{x, y, z\}$ are the values measured on each of the three Cartesian axes.

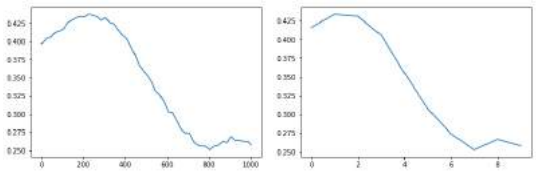
Several time window sizes were explored based on the following considerations. Firstly, a small time window prompts location updates at higher frequency over a small time windows. The second consideration was inference time, a large time window although might yield better estimation, it requires more computation resources for one inference, because it needs to connect more artificial neurons (more connections) to a large input size, compared with fewer needed for smaller time windows. At the other extreme is estimation accuracy, which benefits from a larger time window to capture more relevant information from signal. In this trade-off we chose 4 time windows of 10ms, 100ms, 1000ms and 2000ms, which are presented further in the experiments section. We also consider the case of time window overlapping (with 10%, 50%, 90%) to increase the frequency of location updates for a more responsive systems. Overlapping windows are also useful for LSTM models since information from previous time windows are reinforced over several instances for better predictions.

To improve forward-pass speed, we also explore down-sampling, or compressing the input over the same time window. Figure 4 shows the magnitude value of an accelerometer with 1000 data point (1000ms) on the left side and down-sampled by 99% linear compression to the right, where we can observe that signal trend is retained at this high compression rate, as also observed from a larger time window of 7s in Figure 4(b). The other sensors have a similar performance with down-sampling.

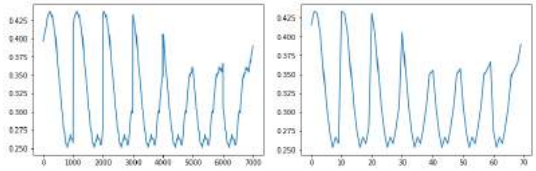
C. Calibration of Recurrent Neural Networks

We experiment training LSTMs under different parameter conditions to identify the best configurations on inertial sensor data (tuples of acceleration, gyroscope and magnetic field). We collect a dataset of 9366 instances (split with a ration 8:5:1 between training, validation and test).

1) Time Window: Inputs to LSTM are sampled over a time window and a well selected size offers enough information to the model for location estimation. A larger time window



(a) Sensor values down-sampled (99%) on 1s time window.



(b) Sensor values down-sampled (99%) on 7s time window.

Fig. 4. Down-sampling sensor values to 99% fewer data points for accelerometer on 1s and on 7s time windows, showing that general signal trends can still be observed even with a heavy compression rate.

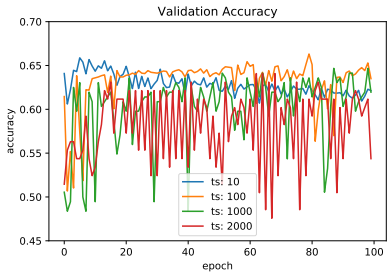
TABLE I
NEURAL NETWORK TRAINING PARAMETER SETTINGS

Parameter	Settings
Epoch	100
Batch Size	100
LSTM Hidden Units	128
LSTM Layer	1 Layer
Learning Rate	0.005
Learning Rules	RMSprop
Training Data	One Round

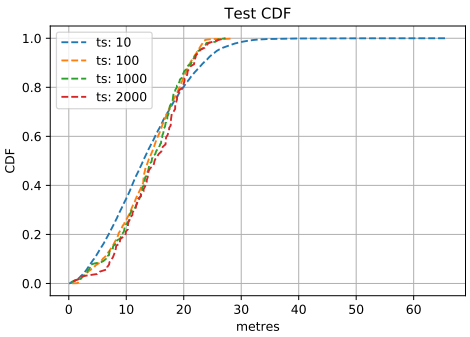
exploits larger scale observations, which could prove more reveling for some movement patterns, although being computationally demanding to perform inferences on a mobile device, with less frequently location updates. In contrast, a smaller time window captures limited information causing difficulty in discriminating between similar activities like moving on a flat surface and climbing stairs, although requiring less computations due to a smaller input layer.

We evaluate different time windows by trained the model with instances capturing 10ms, 100ms, 1000ms and 2000ms of sensor samples, using the training configuration indicated in Table I. Figure 5 presents the training with different sizes of time window. The 10ms input size performs the best on test, with a median error lower than for the other three sizes (error computed as euclidean distance between estimation and ground truth). This is because a smaller time window produces more estimations which falls closer to the ground truth than the other time windows, although differences between time windows are minimal as observed in the Cumulative Distribution Function (CDF) plots in Figure 5(b).

The 1000ms based model indicates a good performance on our evaluation data set and given this larger time window captures more variations and different activities relevant when transitioning between floors (climbing stairs), we select this time window size to use in the following experiments.



(a) Validation accuracy during training



(b) Test set CDF

Fig. 5. Model performance on data input capturing different time windows.

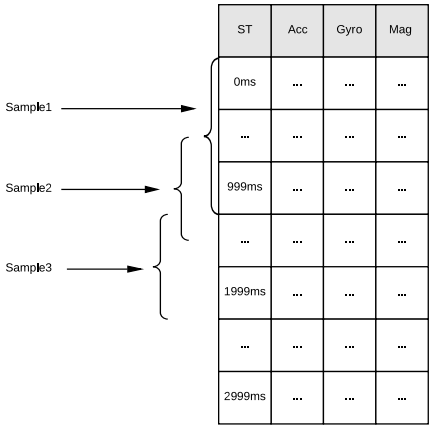
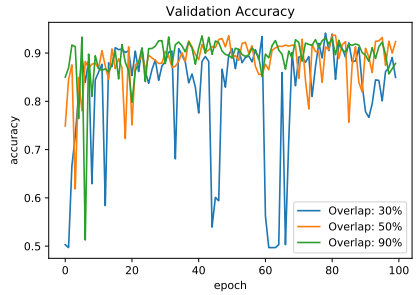


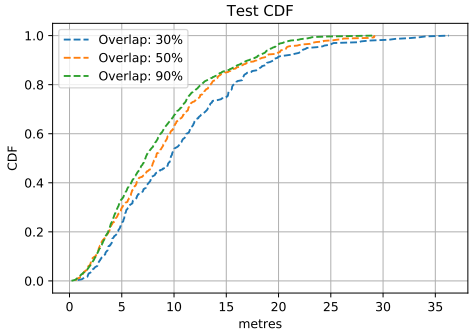
Fig. 6. Overlapping time windows with a ratio of 50%

2) Overlapping Time Windows: This experiment presents the impact of using samples with overlapping time windows. The overlapping ratio experimented with are 30%, 50% and 90%, which increase the amount of training data subsequently by 1.3x, 2x and 9x respectively. Figure 6 shows time windows overlapping each other by 50% (each sample containing half of data points from previous sample and half new ones).

There are two main reasons for using window overlapping. The first is to enhance dependency between consecutive instances by exposing repeated information in the overlapping parts. For LSTM models, this has the role of strengthening through memory adjacent actions and features over consecutive inputs. Secondly, a higher overlap allows us to generates



(a) Validation accuracy during training



(b) Test CDF

Fig. 7. Model performance with different overlapping ratios

more unique instances for training, which is beneficial when starting from a limited dataset.

Figure 7 presents the models trained on data generated with overlapping time windows using the three ratios. In training, the model with data overlapping at 90% performs consistently better than the other two trained with 30% and 50% overlapping data, reaching 90% training accuracy (within one meter to the ground truth), while in CDF performance is also the best with median error just above 5 meters (Figure 7(b)). This is an impressive result considering that it is based on nothing more than inertial sensor data, with relevant calibration points extracted from sequence of unique signal characteristics. From this experiment we observe that a higher overlap in consecutive samples is beneficial to strengthening adjacent patterns, not neglecting that it produces more samples to train on. An overlapping of 90% has the best performance, so we adopt this data preprocessing in following experiments.

3) Reducing Input Size: As observed from Figure 4, moderate down-sampling of data points has minimal impact on preserving information and signal trends, so a relevant exploration is to observe the impact of input compression. By using Principal Component Analysis (PCA) transformation on input data, instances can be compressed even further, with the benefit of producing a smaller neural network model since LSTM internal networks are proportional to input size. On applying PCA to a vector of sensor samples, new variables in a lower dimension are calculated based on eigenvalues and eigenvectors, which retain the relevant information needed by a model to perform efficient estimations. We compare

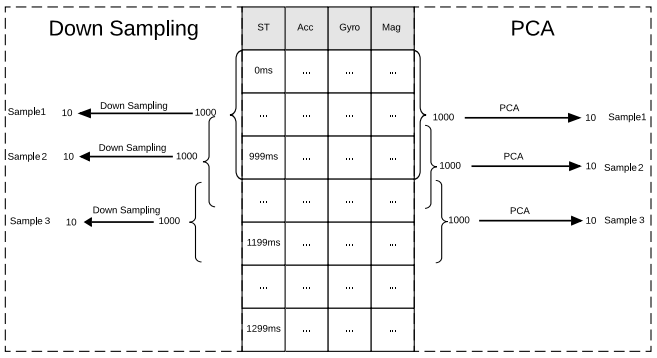


Fig. 8. Down-sampling and PCA with 90% overlapping samples.

the performance of LSTM models taking as input instances after down-sampling (by superimposing a lower sampling frequency on the available data) and with PCA for sample compression. With down-sampling, the size of input is reduced to $10 * 3(axis) * no\_sensors$. For fairness, we constrain the PCA to use the same number of samples after compression.

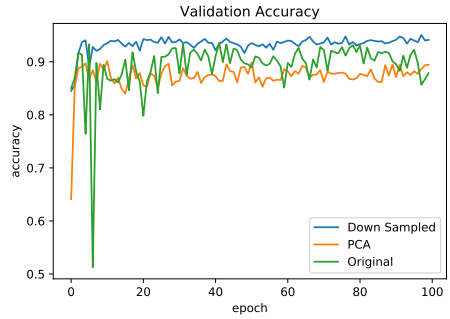
Figure 8 presents down-sampling (filtering data points to a 10 Hz frequency) on the left side, with 90% samples overlapping. By this, one sample is down-sampled from the size of (1000,3) to (10,3). The process of reducing sample size from (1000,3) to (10,3) with PCA is presented on the right.

Both of these input reduction methods are advantageous to propose a more efficient model from a computational perspectives, since the input size is 100× smaller, the size of internal LSTM neural structure is also smaller, leading to more efficient models that can run with lower drain on mobile devices and are also trained faster. The other consideration is prediction accuracy.

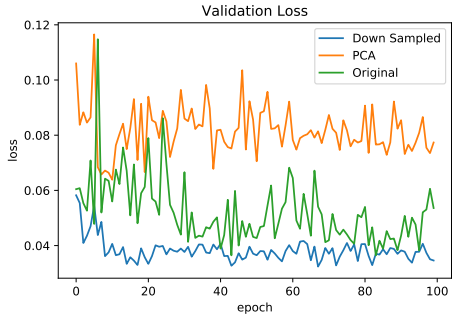
Figure 9 shows the comparison between down-sampled input model and PCA input model with an overlapping of 90% between consecutive instances. In Figure 9(a) we observe a faster convergence rate for down-sampling, reaching 95% of the validation accuracy after just eight epochs and then retaining high accuracy. PCA input model has a lower accuracy rate at around 87%. This can be due to better time correlations in the down-sampled input. Figure 9(b) presents the down-sampled input model converging rapidly from a validation loss of 0.06 to 0.005 within 20 epochs. PCA based model has a larger validation loss of 0.08.

Figure 10 presents the performance for these trained models in a CDF format on the validation set and test set. Both experiments demonstrate that an LSTM model using down-sampled input performs better than the unaltered input model, with a median accuracy of 8 metres on the test set. A model using PCA inputs performs similarly to the unaltered input model for both validation and test sets.

In general, the model using down-sampled inputs has a better accuracy than that of a model using PCA inputs and better than a model using the unaltered inputs. In fact, PCA performs least well, which could be due to loss of relevant



(a) Validation Accuracy



(b) Validation Loss

Fig. 9. Model performance of input data down-sampled, PCA on input data and original data

information during transformation. On the other side, down-sampling inputs retains the trend and shape of movement as observed in Figure 4. This transformation is also better for energy savings due to fewer computations performed on a smaller input size.

4) Summary of RNN for Inertial Sensors: We first determine a suitable time window size from 10ms, 100ms, 1000ms and 2000ms. With all time windows performing roughly the same, we adopt 1000ms windows because this allows more sensor samples to be captured for distinguishing between very similar actions. Through samples overlapping we observe an increase in performance for a higher overlap (90%), which is due to enhancing exposure to relevant events across multiple samples and for enlarging the training set by generating more overlapping instances from a fixed dataset. To reduce the complexity and the training time of models, we compress the input size by down-sampling and PCA dimension reduction, observing that trained models with down-sampled inputs achieve the best performance.

Figure 11(b) presents the performance of all trained models, with CDF generated on the test set. An LSTM model using down-sampled inputs with overlapping of 90% has the best performance regarding the convergence rate and prediction accuracy, achieving a maximum prediction error of just 6 metres and median error below 5 meters.

D. Transfer Learning

We evaluate proposed LSTM model using down-sampled inputs for robustness across different devices – training with data from one and transferring the model to another phone. We collected two rounds of sensor data with the entry-level phone, Smartisan, and with the flagship phone, OnePlus. Data from Smartisan is used for training the model under the conditions and parameters identified above. Thus, no sensor data from OnePlus is used in the training set. We test both models trained for down-sampled inputs and for PCA based inputs. Figure 12 shows the results in CDF format for testing on the same phone used in data collection, Smartisan and also for transferring this model and testing on data from OnePlus. We observe that transferring the model between devices succeeds, obtaining very similar performance between the two test sets. As observed before, models with a down-sampled input achieve better performance.

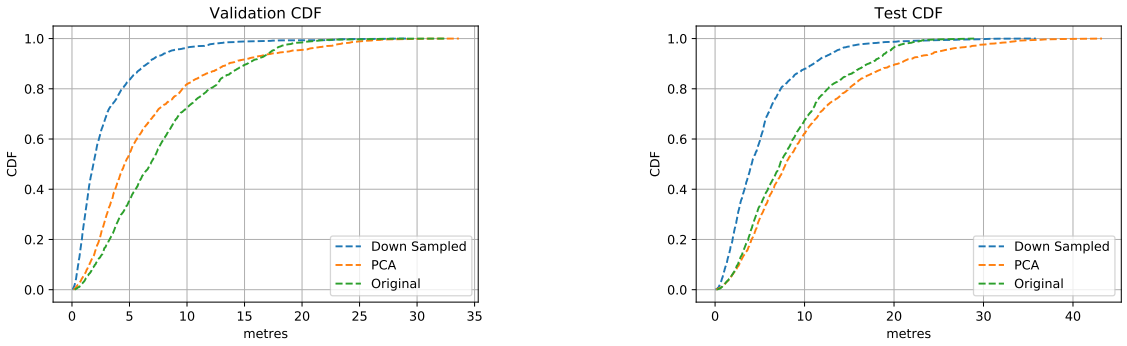
The results of our transfer learning experiment are plotted on the floor-map. In Figure 13(a) the estimated trajectory of the phone used for training (Smartisan) is presented with an orange color. This is very similar to the corridor shape (grey path) and across the large room to the right of the track. Operating at 90% samples overlap permits a more granular location estimation. Figure 13(b) presents the estimated trajectory of the OnePlus phone by using the model trained on the Smartisan phone. This transferred model shows a good generalization by estimating the trajectory reliably with a few exceptions in the open areas, but it realigns with this exact path fast on incoming observations.

IV. Discussion

Recurrent Neural Networks have an advantage over simple Dead Reckoning approaches since they track the estimation not just from the last location as done with dead reckoning, but considering longer stances of observations in the past offered by the long-term memory mechanism. This compensates for local distortions and imperfect observations in sensor data, which is not available to dead reckoning approaches easily.

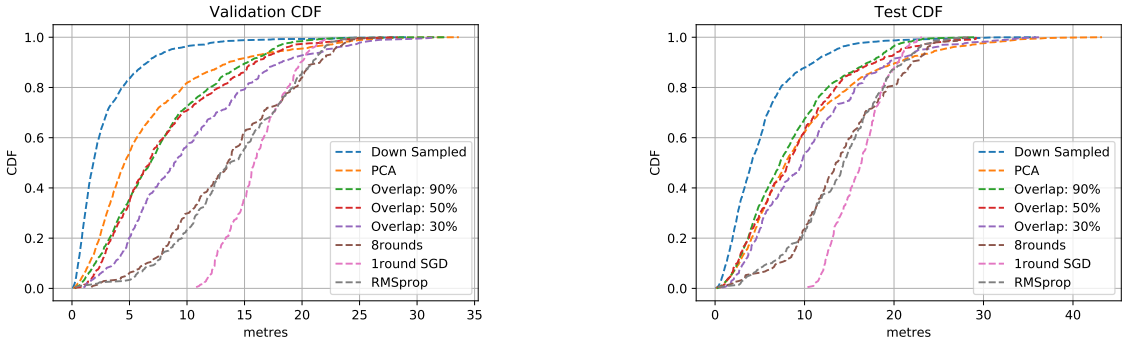
Previous solutions based on signal processing have been developed when data was scarce and mathematical modeling was the standard. However, with the increasing availability of data, which is hard to model entirely with precise mathematical formulation, deep learning adoption offers the benefit of extracting complex features automatically from data. While we move the complexity of modeling to generating good quality labeled data for training, we believe this is achievable with ingenious solution to facilitate data collection and labeling such as using camera infrastructure opportunistically [7].

In future work we will integrate the inertial sensing modality explored here, with other type of sensing modalities, like WiFi fingerprinting, using modality specific neural networks. The advantage of proposed use of LSTM on inertial sensors is that gradients can flow similarly in other portions of a network architectures, making integration with diverse sensing modalities easy an elegant, such as using multi-layer perceptions for WiFi fingerprints in a multimodal architecture.



(a) Validation CDF (b) Test CDF

Fig. 10. CDF of down-sampled and PCA transformations and of original data format as inputs to LSTMs.



(a) Validation set performance for varying overlap (b) Test set performance for varying overlap

Fig. 11. Different levels of overlapping showing that training is robust on unseen test set matching in performance with validation set.

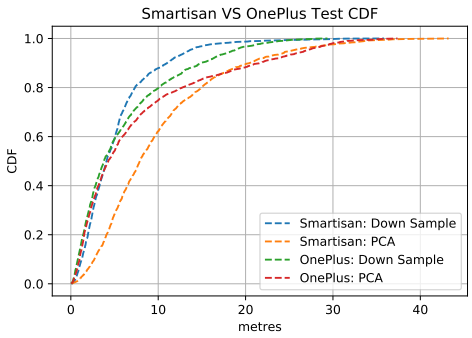
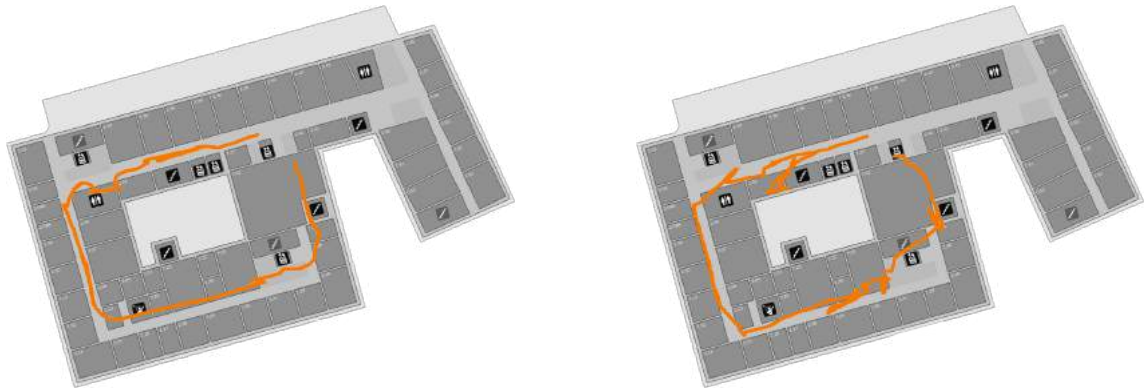


Fig. 12. Evaluation on test sets collected with two different devices of a model trained with data from just one and performing transfer learning to the second.

V. Related Work

Without the availability of GPS for tracking as in outdoors [12], indoor tracking is performed by inertial sensors in dead reckoning systems [2]. Inertial sensors achieve this by characterising pedestrian gait cycle [13] and direction of movement [14, 15] to build the trajectory relative to a starting position. As presented by Xiao et al. [16], there are three important aspects to inertial motion sensing: motion mode recognition, orientation tracking and step length estimation. Motion recognition from acceleration data has been modeled with simpler classifiers [4], and its been shown to be body attachment sensitive, which is hard to model accurately [17]. Orientation is commonly performed by combining magnetometer and gyroscope data, as presented by Huyghe et al. [18] using a Kalman filter and using deep learning [19]. Unlike all these systems, we leave the mechanics of motion to be automatically discovered by the LSTM from data. LSTMs for location estimation have been used before by Walch et al. [20] although their input consisted of camera images alone and by Wang et al. [21] using magnetic and light sensors.

To reduce the problems of inertial sensing (drift, device calibration and noisy samples), many solutions choose to rely on periodic anchor points by observing unique characteristics of the signal [4], ambient conditions [3, 5] and in combination with other sensors, most commonly with WiFi [6, 22]. We rely entirely on inertial sensors without such imposed calibrations, noticing that LSTMs identify unique signatures in these signals (similar to reference points in previous methods although extracted automatically here), which helps estimations to recover from occasional bad drifts.



(a) Location Estimation with Smartisan

(b) Location Estimation with OnePlus

Fig. 13. Location prediction (with orange) overlapped to building map for a walk on a path on corridors clock-wise starting from the top right corner in the central part of the building, performed with two different phones. This shows that training with one phone (a) and testing with another (b) still provides good estimations.

VI. Conclusions

In this data focused age each research field is adapting to exploit the increasing availability of data. This should also be the case with indoor positioning and navigation suitable to learn directly from data with scalable and robust deep learning models. In this work we demonstrate this to be achievable by adopting a recurrent neural network (LSTM) to track the location of a smartphone based on its inertial sensor data alone. We train several LSTM models using different data preprocessing options and model configurations to offer an insight into how these can be tuned for improved their prediction accuracy. We achieving below 5 meters of median error using LSTM models that are lightweight to run on mobile devices and demonstrate these are transferable across devices.

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