Neural Network Fingerprinting and GNSS Data Fusion for Improved Localization in 5G

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2021 International Conference on Localization and GNSS (ICL-GNSS) | 978-1-7281-9644-2/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICL-GNSS51451.2021.9452245

***Abstract*—In modern radio networks with large antenna arrays and precise beamforming techniques, accurate user positioning plays a key role in enabling seamless mobility management, link optimization, navigation and safety control. In open and rural areas, Global Navigation Satellite Systems (GNSS) are able to provide high-accuracy and high-reliability positioning performance. However, in urban and densely built-up areas the GNSS performance is typically substantially degraded due to rich scattering and multipath propagation effects. In this paper, we propose a machine learning based solution to boost positioning accuracy in urban areas by (i) obtaining User Equipment (UE) position from beamformed Radio Signal Strength (RSS) measurements and (ii) coherently fusing it with GNSS-based positioning data to enhance overall positioning performance. Based on the obtained numerical results, we were able to achieve a meter-level accuracy with the proposed machine learning model utilizing the beamformed RSS measurements, and subsequently improve the positioning accuracy further via fusion with GNSS data.**

***Index Terms*—5G, beamforming, deep learning, fingerprinting, positioning, sensor fusion**

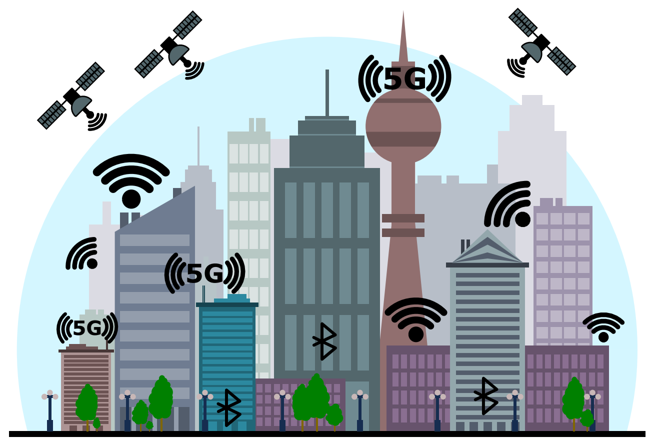

Fig. 1. Example urban environment with heterogeneous network deployment

I. Introduction

Modern radio networks with beamforming technology enable greatly improved throughput, enhanced connectivity and high spectrum efficiency. On the other hand, the new performance requirements together with high complexity of the network demand numerous enabling technologies. One of such requirements is being able to localize and track the mobile User Equipment (UE) at all times in order to provide location-based services and utilize location-awareness in network operations. This work focuses on UE localization in densely built-up areas, in which Global Navigation Satellite System (GNSS) reception suffers from blockage or multipath propagation resulting in poor GNSS localization accuracy. These areas are also densely occupied with numerous wireless networks, including cellular (5G, 4G), Wi-FI, Bluetooth, LoRa, etc., as demonstrated in Fig.1, which we can use for localization. Processing capabilities on the network side and the UE side enable utilization of the aforementioned heterogeneous wireless network signals to perform positioning. The capabilities, techniques and approaches for network localization were surveyed in [1], presenting state-of-the-art of cellular and Wireless Local Area Network (WLAN) positioning, as well as related topics including indoor mapping or mobility state estimation using Radio Signal Strength (RSS) data. The paper shows the existing work on positioning data fusion. It is nowadays commercially available in e.g. SiRFstarV architecture, combining GNSS, Wi-Fi, cellular and multiple sensor systems for localization purposes [2], but requires a dedicated chip on the device. The variety of position-related radio measurements including Time of Arrival (TOA), Time Difference of Arrival (TDOA), Round Trip Time (RTT), Angle of Arrival (AOA) or RSS can be combined in fusion systems [3], while the fusion itself is usually performed by Bayesian methods such as various Kalman Filters (KF) or particle filters [4]. Alternatively, sensor fusion can be performed using machine learning methods, as is the case in this work. Additional noteworthy surveys on indoor localization and sensor fusion include [5] and [6].

In this work, we demonstrate the RSS-based UE localization in 5G cellular urban deployment with multiple access points (APs) representing base stations (BSs). To boost localization accuracy further, we are later combining the available location data from multiple sources (in this case with GNSS-based location). The RSS-based positioning approach is chosen, since RSS measurements are easily accessible and are in any case continuously measured by the network during common networks operations, such as mobility management. For both RSS-based UE localization and GNSS data fusion, we utilize artificial neural network (NN) models as general-purpose regression models.

The main contributions of this paper are as follows:

1) We demonstrate the efficiency of machine learning so-

lutions, namely densely-connected NN, for RSS-based UE localization in dense, beamforming-based network deployment under high RSS uncertainties.
2) We propose a NN fusion model, combining localization data from multiple sources, such as RSS and GNSS, to boost the positioning accuracy.
3) We discuss the importance and impacts of positioning fusion in urban scenarios with modern radio networks and provide the relevant references in the literature.

The rest of this paper is organized as follows: Section II discusses the RSS-based positioning idea and approaches, Section III describes the GNSS data synthesis and data fusion approaches, Section IV presents the system parameters and the simulated deployment of our experiment. Finally, Section V shows the numerical results and Section VI discusses the future work and concludes this work.

II. RSS-BASED POSITIONING

The first objective addressed in this paper is to obtain the accurate positioning information in 5G New Radio network with no access to auxiliary positoning data, such as GNSS. There are numerous instances, where the UE does not or cannot receive satellite data, such as lack of reception, faulty or absent GNSS receiver, or turned off module in order to save battery power.

In recent decades, obtaining positioning information from RSS data was thoroughly investigated, mostly in scope of indoor positioning systems (IPS), where model-based methods fail to yield accurate results due to strong scattering and multipath effects, as shown in e.g. [7]. The model-free techniques based on fingerprinting idea are widely utilized, as they provide reasonably accurate positioning results with little effort and only a few challenges. The main idea of fingerprinting is to map a set of RSS measurements to a specific location based on pre-collected RSS measurement data from the target area.

The noteworthy challenges include optimizing the processing time [8], as fingerprinting databases are voluminous with large amount of individual fingerprints, keeping the database up-to-date and finding and creating the proper search algorithms [9]. Solving and optimizing the challenges is crucial in order to operate system effortlessly, efficiently and with accurate results. Additional important characteristic of fingerprinting approach is that it offers the area-specific solution, and extending the coverage increases the complexity, storage and processing requirements of the fingerprinting system [10]. The classic fingerprinting is highly vulnerable to any changes in the environment, since any changes in propagation patterns result in outdated fingerprinting database.

Traditionally, the fingerprint-matching algorithm compares the newly arrived measurement of RSS data with the fingerprints in the database, and based on the chosen hyper-parameters and distance to the entries in the database estimates the UE location. Furthermore, the fingerprinting approach utilizing neural networks is proposed in numerous publications, including [11], which compared the performance of a convolutional neural network with a random forest classifier and shows that dynamic changes in the channel destabilize the performance of the system. Sub-meter indoor positioning accuracy is achieved in [12], while utilizing NN architecture and combining Wi-Fi and LTE channel measurements. NN-based fingerprinting approach in [13] utilizes spatial beam Signal-to-Noise Ratio (SNR) as input data instead of conventionally used Channel State Information (CSI) or Received Signal Strength Indicator (RSSI) on Wi-Fi measurements and achieves centimeter-level accuracy on their dataset. A paper focusing on NN positioning in 5G [14] achieved 1-1.5 m mean positioning error in beamforming-enabled simulated network, while [15] tested the performance of Extreme Learning Machines (ELM) in 5G deployment. Different reference approaches of non-GNSS positioning are presented in Table I, highlighting the utilized positioning algorithm, scenario of interest and reference data.

TABLE I
NON-GNSS POSITIONING APPROACHES.

Reference	Pos. algorithm	Scenario	Reference data
[10][9][8]	k-means, k-NN	Indoor	Wi-Fi RSS
[11]	NN, RF	Indoor	Wi-Fi CSI
[12]	NN	Indoor	RSS
[13]	NN	Indoor	Wi-Fi beam SNR
[14]	NN	5G Outdoor	RSRP
[15]	k-NN, ELM	5G Outdoor	CSI
[7]	Path loss	5G Outdoor	TDOA
[16]	Extended KF	5G Outdoor	beam-based AOA

In this work, we utilize the artificial NN to serve as the bank of measured fingerprints, and the prediction algorithm at once. Thanks to the property of NNs to generalize, the solution is robust to the dynamics in the environment, and it is able to update the ”database” with new fingerprints, as well as to scale to larger target areas without drastically increasing the complexity. For characterizing and evaluating RSS positioning, we tested a range of alternative regression methods, including k-NN regression, decision trees and related ensemble-based regressions, and Support Vector Machine regression (SVR).

The most commonly utilized approach for fingerprinting, k - Nearest Neighbors (k-NN), is able to achieve excellent results, but has two major drawbacks, which make it unsuitable for the considered scenario. Firstly, it is unable to generalize otherwise than by averaging between training data samples, and secondly, the processing time of predictions significantly increases for voluminous databases covering areas larger than, e.g., a single building. There are numerous works addressing the processing speed optimization [10], [8], but the underlying challenge of processing large amounts of data in prediction phase remains.

Decision tree and related ensemble-based regressors such as random forest offer similar, at times better performance than k-NN, but face similar drawbacks regarding generalization and operating with voluminous data sets. The general idea behind the approach is in building decision trees with target labels in leaf nodes. SVR with various kernel functions is a potent and solid method for regression tasks, but struggles when the number of samples is larger than tens of thousands. It is also limited to a single-label output, and therefore predicting longitude and latitude with SVR requires two separate models.

Utilizing NNs for the task, as proposed in this paper, overcomes the aforementioned challenges faced by the above-discussed methods. Large amount of data is merely a positive aspect when training a NN, and generalization can be achieved by appropriately fine-tuning the model. The challenges that have to be addressed when utilizing a NN regressor are optimizing the model architecture and hyperparameters, finding the computational resources to train the model, and ensuring that the overfitting and underfitting of the data does not occur. We also evaluated the performance of convolutional NN architectures, but weren't able to achieve better performance than that of models with only densely connected layers on given data.

III. Positioning model fusion with GNSS data

Although the novel GNSS systems are capable of reaching centimeter-level accuracy in theory, real-world performance in non-line-of-sight (NLOS) scenarios is often significantly worse. On top of that, 5G-enabled novel technologies such as self-driving cars or unmanned aerial drones, in which high-accuracy localization and tracking are mission-critical, demonstrate use cases where failures may result in tragic events and endanger people's lives. In addition, relying on GNSS-only positioning makes such systems susceptible to GNSS jamming, spoofing, or signal unavailability in e.g. tunnels.

Combining information from multiple sources leads to increased performance of the system, as shown in [6] or [1]. Direct type of information fusion is widely used across positioning methods, while having wide success in vehicular positioning and autonomous driving area. Combining GNSS positioning with multitude of sensor measurements such as speed, direction, etc. is studied in [17], significantly improving the positioning accuracy. Moreover, a combination of Global Positioning System (GPS) and ultra wide band (UWB) positioning is utilized with wearable devices in [18], where the authors highlight the system weakness to observed measurement uncertainties.

In this work, we consider a generation of synthesized GNSS data, which introduces realistic positioning errors for urban scenarios. In order to generate such data, we utilized the smartLoc dataset [19] collected from Berlin, Germany. The dataset consists, among other measurements, of mass-market GNSS receiver measurements together with high-accuracy Real Time Kinematic (RTK) GNSS receiver recordings, which is able to serve as ground truth. In order to synthesize the error, we calculated the positioning error between the two synchronized recordings and calculated the second-order statistics to reveal the error correlations. We then applied the synthesized error to our ground truth data, and as a result we obtained the GNSS-like position measurements in the considered deployment.

IV. Proposed NN models for positioning and data fusion

In the following, we first introduce the proposed NN model for stand-alone RSS-fingerprinting-based positioning. After that, we present the proposed approach for the fusion model, which is able to combine the possibly available GNSS-originated positioning information with the RSS-based data.

A. RSS fingerprinting NN model

Each source of positioning data has its own independent positioning model. In case of our 5G network it is a sequential NN model with 3 hidden layers, which takes one array of measurements as the input and returns a prediction of current position as the output. Here, the measurement array refers to beam-wise RSS measurements obtained from the synchronization signal blocks (SSBs) as defined by 3GPP [20], transmitted by each AP as described in Section V-A. Moreover, the proposed NN model for the RSS-based positioning has the following architecture:

- Input layer with 224 inputs for 7×32 antenna array measurements
- Densely connected layer with 1024 neurons and Rectified Linear Unit (ReLU) activation function
- Dropout layer with 0.2 dropout rate
- Densely connected layer with 1024 neurons and ReLU activation function
- Dropout layer with 0.2 dropout rate
- Densely connected layer with 1024 neurons and ReLU activation function
- Dropout layer with 0.2 dropout rate
- Densely connected output layer with 2 neurons and linear activation function for RSS positioning prediction

The model is trained with Mean Squared Error (MSE) loss, as it represents the Euclidean distance between the UE positions and Adadelta optimizer [21]. This optimizer is based on the stochastic gradient descent with two major advantages, namely automatic initial learning rate selection and continuous learning rate decay capability, which offers more delicate model tuning the later the epoch. The same NN model architecture was trained for 200 epochs at each measurement uncertainty level, which represents the quality of the RSS measurements, as discussed with numerical results in Section V.

The proposed RSS fingerprinting approach performs the localization sample-wise, with no temporal dependency accounted between measurements. The dropout regularization was applied to mitigate overfitting, resulting in same-level performance on training and validation data sets in training, as well as on the testing dataset during model evaluation.

B. Positioning fusion NN model

A fusion model, which is able to combine the information from the RSS-based positioning and GNSS data, is a 2-layer NN concatenating up to 20 recent positioning measurements from each available source, taking advantage of (i) source diversity, as well as (ii) temporal diversity of position. It has the following architecture:

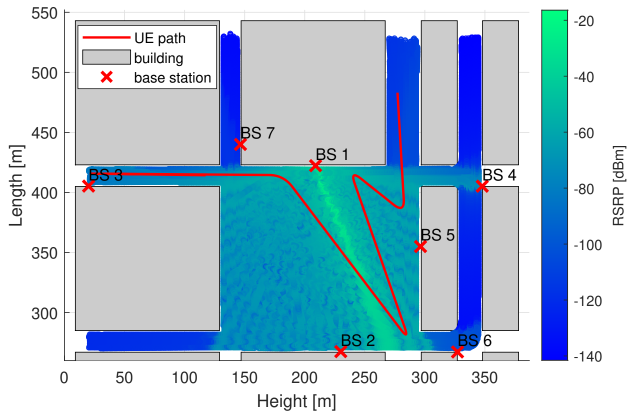

Fig. 2. Urban area network visualization with 7 beamforming-capable BSs deploying 224 beams. A single UE is moving through the environment (red line) collecting the measurements.

- Two input layers with (20,2) input shape each for recent RSS positioning NN model predictions and GNSS positioning data
- Concatenate layer, merging the two inputs
- Densely connected layer with 128 neurons and ReLU activation function
- Densely connected layer with 128 neurons and ReLU activation function
- Densely connected output layer with 2 neurons and linear activation function for current position prediction

The chosen model hyperparameters were MSE training loss, Adadelta optimizer and 200 epochs training duration. The model is built in semi-sequential manner, where every positioning source (in this case only 2, but in practice the model can be extended) has its own input. On top of that, the model considers the positioning inputs from previous iterations (up to 20), which add temporal information to the model and thus enable to cope with source-specific uncertainties better. The dropout regularization was removed from the model, as the regularization was achieved by various uncertainty types in the input data.

V. Numerical results and analysis

A. Simulation environment

In order to establish a realistic and well-justified simulation environment, we consider a ray-tracing-based simulation setup using the Madrid grid layout, as proposed by METIS society in [22]. This layout introduces a rich urban environment with varying street widths and open areas, which enhance the generalization and scalability of the used setup. Considering a specific segment of the Madrid map, 7 APs operating at 30 GHz carrier frequency are deployed in such manner that they together provide a suitable coverage throughout the deployment area. Each AP is equipped with an antenna array of 32 elements in a shape of uniform linear array with horizontally mapped elements.

TABLE II
Mean error comparison of the deployed models

Uncertainty level	0	1	2	3	4	5
Model	RSS fingerprinting NN model					
Mean error [m]	1.09	1.32	1.86	2.53	3.10	3.40
Model	Positioning fusion NN model					
Mean error [m]	0.74	0.77	1.02	1.23	1.66	1.75
Error reduction [%]	32	42	45	44	46	49

The simulated RSS measurement data is based on beam Reference Signal Received Power (RSRP) measurements obtained by the UE from the SSBs transmitted by each AP over 32 beams. The beamforming used with the SSB transmission is implemented according to the phased-array principle. Moreover, the used beam set is designed based on the discrete Fourier transform matrix, which provides an orthogonal beam set with efficient beam coverage in angle domain. Furthermore, the beam-wise RSRP measurements at the UE are derived from the channel estimates of the received SSBs, which have been conveyed through a ray-tracing tool, as proposed by METIS and 3GPP in [23] and [24], respectively.

During the simulation, the UE moves in the deployment area with an average speed of 5 km/h, varying based on the curvature of the turn, on a constant 1.5 m height above ground, while collecting measurements at approximately 0.36 s intervals. In total 1 342 701 measurement samples were generated, where each sample consists of the UE position and the obtained beam-wise RSRP measurements. An illustration of the simulation scenario is shown in Fig. 2, where also RSRP values of a single beam at base station #1 (BS1) are demonstrated together with an example UE track.

For each sample, we also added the GNSS-originated position estimate to the data set, as described in Section III. The data set was then split to training, validation and testing subsets in 60-20-20 ratio without shuffling, to retain the sequential information in the data.

To evaluate the system's ability to suppress measurement uncertainties such as noise, interference, shadowing or other channel effects, we additionally added the artificially generated uncertainties to the RSS measurements. The uncertainties follow Normal distribution $\mathcal{N}(\mu, \sigma^2)$ with mean $\mu = 0$ and standard deviation $\sigma \in \{0, 1, 2, 3, 4, 5\}$ given in dB-unit, and serve as additional error caused by a mixture of additional body shadowing, signal interference, or receiver / transmitter antenna imperfection. As a result, we obtained 6 data sets with different levels of measurement uncertainties.

B. Positioning results

In this section we present the numerical results of our positioning models. We trained the same model architectures on each of the 6 data sets with varying uncertainty strengths to evaluate the models' capability to suppress measurement uncertainty and generalize. The presented results illustrate the performance of both the proposed RSS fingerprinting NN

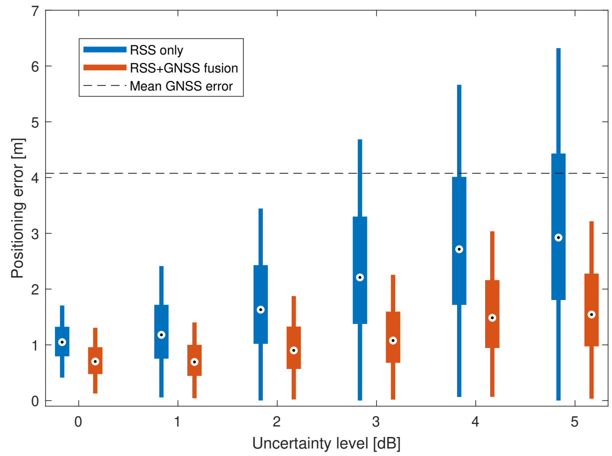

Fig. 3. Positioning error comparison for different uncertainty levels in RSS measurements for both RSS fingerprinting NN model and positioning fusion NN model. Here, the box shows the 50% confidence interval, and the whiskers show the 95% confidence interval bounds of the error.

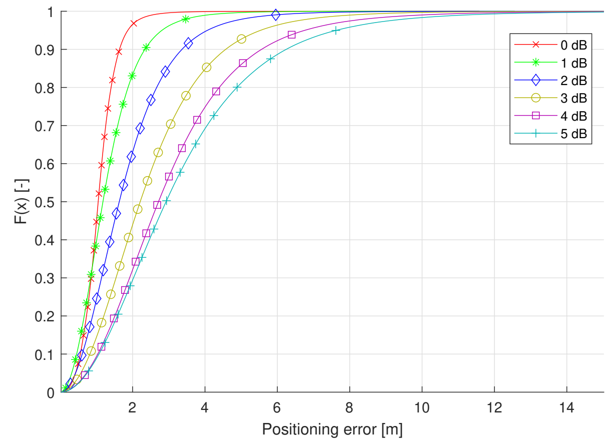

Fig. 4. eCDF of positioning prediction errors of RSS fingerprinting NN model.

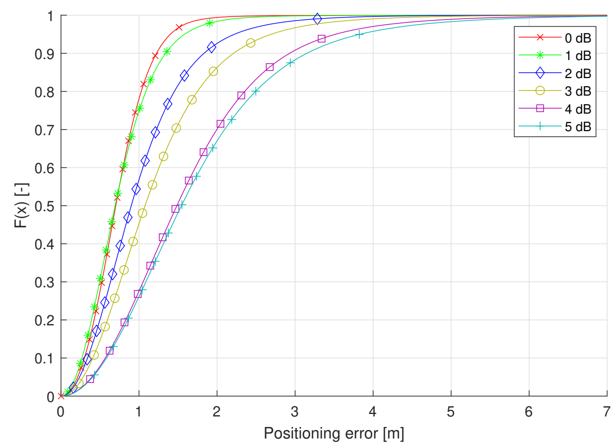

Fig. 5. eCDF of positioning prediction errors of positioning fusion NN model.

model and the corresponding positioning fusion model with GNSS on the given data set.

The mean positioning errors for the RSS fingerprinting NN model and the associated fusion model are shown in Table II. To compare, the mean GNSS error on the dataset is 4.08 m. In addition, also the percent of positioning error reduction introduced by to the fusion model is provided. The results show, that the fusion model is able to significantly reduce the positioning error when compared to the RSS fingerprinting model by up to 49%. Whereas the RSS fingerprinting NN model is capable of achieving meter-level positioning accuracy on uncertainty-free data, the fusion model further reduces the error, resulting in sub-meter positioning accuracy results for both 0 dB and 1 dB measurement uncertainty case. As expected, the significance of the fusion model is substantially increased together with growth of measurement uncertainty.

In order to further evaluate the positioning error statistics, Fig. 3 presents the positioning error statistics of the proposed RSS positioning model (blue) and positioning fusion model (orange) as a box plot. The centre of each box marks the median error, whereas the box shows the 50% confidence interval and the whiskers indicate the 95% confidence interval of each prediction. The figure reveals, that apart from significantly reducing the positioning error, the fusion model strongly suppresses the range of prediction error, especially at higher uncertainty levels. This is of great importance especially in mission critical use cases, where the high-accuracy positioning is desired to be sustained ubiquitously over time.

For revealing the detailed statistics of the position estimate errors of both models, we also study the empirical Cumulative Distribution Function (eCDF) of the model predictions. Thus, Fig. 4 shows the positioning error distributions of RSS fingerprinting model for the considered uncertainty level scenarios. The resulting distribution resembles a folded normal distribution (absolute value of normal distribution) and with increasing uncertainty strength, the error statistics steadily increase. Furthermore, the eCDF curves of separate uncertainty levels are ordered in consistent manner according to the corresponding mean errors, shown earlier in Table II. Consequently, Fig. 5 shows the corresponding eCDF error curves for the proposed fusion model, which is able to greatly improve the positioning capabilities in the area of interest. With the exception of positioning accuracy values, the error curve shapes appear quite similar with the corresponding curves of RSS fingerprinting model. However, interestingly there is significant similarity between the error curves of 0 dB and 1 dB uncertainties, as well as the error curves of 4 dB and 5 dB. Overall, the results indicate a great performance potential of coherent data fusion, even under high uncertainty values and low-complexity positioning models.

VI. Conclusions and Future Work

In this work, we presented a method to improve the localization accuracy in urban and built-in areas by obtaining positioning information from various signals of opportunity, such as the considered 5G RSS measurements, and subsequently performing a positioning fusion to coherently combine position information from other sources, such as the GNSS. We discussed the state-of-the-art methods for acquiring positioning data from various radio measurements, and the approaches to combine such measurements to increase the system performance. Regarding the positioning solution, we proposed two NN models, first serving as a RSS fingerprinting model and the second one as a positioning fusion model, which combines sequential outputs of the first model with the available GNSS measurements. For obtaining the presented numerical results, we implemented a realistic ray-tracing-based simulation of 5G New Radio signals considering an urban scenario based on the Madrid grid. The received RSS measurements taken by the UE were determined with the ray-tracing tool defined by the METIS society and recommended by the 3GPP. The obtained numerical results show, that the RSS fingerprinting model is capable of obtaining a meter-level accuracy in uncertainty-free scenario, and 3.4 m mean positioning error when the uncertainty of RSS measurements has 5 dB standard deviation. Moreover, the positioning fusion NN model is able to reduce the positioning error by up to 49%, having sub-meter accuracy in uncertainty-free scenario and 1.75 m mean positioning error in 5 dB uncertainty case. In addition, the proposed fusion NN model was able to significantly reduce the confidence intervals of the positioning, which is a great benefit for various use cases, including mission critical services.

The results presented in this paper comply to the 3GPP requirements for 5G, namely a sub-meter level positioning accuracy in the urban areas. Nevertheless, we believe that the positioning performance of both RSS fingerprinting and fusion system can be improved. Simply increasing the dimensions of both NNs will improve the accuracy of the model on the training set, yet on the other hand will make the models more prone to overfitting, which is problematic especially if the training set has limited number of samples. We also believe, that utilizing convolutional NNs for RSS-based localization is an intriguing and not yet well-addressed approach in the literature. Since convolutional NNs are able to read the patterns in the data and offer above human-level performance in machine vision and pattern recognition, we are confident that the method can revolutionize the fingerprinting-based approaches as well. The tested convolutional models achieved visibly worse results than the dense ones, but in our future work we will invest in finding the efficient convolutional models for the RSS fingerprinting task. The positioning fusion model can also be optimized by modifying the hyper-parameters and testing different network architectures, e.g. recurrent or long-short term memory NNs. Furthermore, we will aim to create a platform able to utilize the idea of positioning fusion in any scenario, rather than creating a dedicated model for each individual deployment as with the current work.

Acknowledgment

The authors would like to thank the Academy of Finland (grants #323244 and #319994) for their support of this work.

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