Deep Neural Network for Localization of Mobile Users using Raytracing

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***Abstract*—As the world evolves towards faster data transmission, there is an ever-increasing demand for better user localization which will find application in transport, medicine, and robotics. In this study, we present an accurate localization algorithm for mobile users using deep neural network with Bayesian optimization and a communication channel operating at 3.75GHz frequency. We design a deep neural network model which facilitates and speeds up the localization process. The deep neural network (DNN) is utilized in this study to locate moving user equipment (UEs) with randomly assigned velocities. Using preliminary computer simulations, we present a method for training a neural network that extracts channel parameters (features) that are used to estimate location. Our method produces localization accuracy for line of sight (LOS) users, less than 1 m error, and the accuracy can further be improved by implementing higher rate of data sets.**

I. Introduction

Advances in mobile communications are driven by the need to meet higher data rates and wider coverage. A major approach to meet this need is by the use of faster beamforming which provides uninterrupted mobile communications by steering the beam in a desired direction. A base station can be converted into a self-learned network which can provide specific information on user location. This is carried out by a localisation process, which is the process of determining the location of a user within an existing network. In cellular communication networks, a number of algorithms are present to determine user location. Lei Ni et al [1] used signaling data such as Reference Signal Received Power (RSRP) and timing advance to conduct localization. Coluccia et al [2] compared many advanced strategies, including localization using a hybrid Received Signal Strength (RSS) and Angle of Arrival (AOA), projection onto a convex set, multi-hop methods, and so on. The authors of [3] investigate several localization methods based on Time-of-Arrival (TOA). These algorithms, in general, accomplish precise localization by using channel characteristics such as AOA, TOA, RSS, as well as numerous channel statistics obtained from the channel parameters. These approaches, such as the least square methods outlined in [2], frequently involve time-consuming and complex computations. In [4] a geometry-based viewpoint is investigated to increase localization performance utilizing non-line of sight (NLOS) routes. In previous investigations, researchers looked into NLOS components as a source of distortion [5]. However, few Multi path components (MPCs) can be received with large RSS from the NLOS components that increase channel sparsity and hence give extra information on a user equipment's (UE) location [6]. In literature, AOA, TOA, and RSS are the commonly utilized characteristics to predict location. In this study we leverage these features using supervised machine learning (ML) technique (regression method) to improve the localization process for moving vehicles. In supervised learning, It is expected that there is access to a collection of learning characteristics that have been assessed across numerous observations, as well as an outcome variable (in this case, the UE position), also known as the label or the target.

Fig. 1: Ray tracing scenario in the Gilmorehill campus of the University of Glasgow, Glasgow, UK.

II. Methodology

We show how the wireless channel's features and location information generated from a ray-tracing model can be turned into input features and output labels for training a deep neural network (DNN) on the base station (BS) side. To train the DNN model to forecast the position of users, we use raw channel metrics measured at the BS provided by the ray tracing software, such as AOA, TOA, and Received signal strength (RSS). The number of inputs to the model is determined by the number of multipath components (MPCs) used and the number of characteristics examined. We limited the number of MPCs to twenty-five for more realistic scenario. The number of inputs is the product of the number of MPCs and number of features i.e., AOA, RSS and TOA. The output should be the x and y coordinates of a user's location.

To demonstrate localization concept, a small cell scenario that is at the University of Glasgow campus is set up in an urban environment, in Glasgow, Scotland, UK. (Fig. 1) shows the base station, positioned on the university of Glasgow, Gilmore campus buildings. The cell is defined to have a directional antenna for carrier frequency 3.75 GHz (100 MHz bandwidth). Three route receivers were positioned at 2 m height from ground and 5 m apart from each other considered

as moving vehicles along a route at 5, 10, 15 meter/sec through the scene in reference to coordinates (x = -596.64 and y = 139.01m), shown as a red arrow (Fig. 1). The route covers the Byres Road, JMS, library and Glasgow university union (GUU). There exist multiple receivers (red points in (Fig. 1)) on the route similar to work shown in [7], [8] : some receivers correspond to the NLOS path and others correspond to the LOS path. The UE locations within their respective receiver point assist to predict the location as DNN output. Regarding simulation parameters, these devices are specified to have MIMO directional array antennas at both transmitter with 49 dBm transmitter power, 15 degrees down tilted and receiver with -100 dBm sensitivity. Next, an Intel(R) Core (TM) i7-9700 CPU @ 3.00GHz, 32GB RAM PC, and Wireless InSite® MIMO version 3.3, are used to simulate the scenario. This work is inspired from [9] to execute the simulations with more multi-path information on moving users.

III. Result and Discussion

Here we show which channel features and location information are turned into input features and output labels for training a DNN on the BS side. The input features are DOA, DOD, TOA, and RSS which are fed to two hidden layers. Each hidden layer consists of hyperparameters that are 4 to 50 (nodes), learning rate is in range of 1e-3 to 1e-1 and optimized function, through Bayesian optimization approach. The expected output is the x and y coordinates of the route receiver points. The goal of this learning process is to reduce the loss function as much as possible. In this work, we chose the mean error as the loss function. As a learning-based optimization problem, we estimate the position. The purpose of the optimization issue is to find a mapping $\mathcal{F}$ so that the mean error between the known and estimated outputs is as little as possible [9],

$$\min_{\mathcal{F}} \|\mathcal{F}\left(\text{Known values} - \text{Expected values}\right)\|^2 \qquad (1)$$

The deep learning toolbox in MATLAB 2021a was used to create the DNN model. Using the back-propagation approach, the DNN can learn difficult functions with adequate training data. The receiver route at 10 meter/sec speed started from NLOS area (dark zone) and as it approaches to JWS and JMS antennas, it gets in LOS area. When the UE was in NLOS area, it did not receive the optimal signal strength and hence the disparity in the result. However, when it reached the LOS area, the predicted locations are very close to true locations Fig. 2. It is clearly seen that the 85% of LOS user location gets predicted with less than 1m error with respect to its true location. This study encourages us to estimate the future location of the UE as future work. Also, we will implement MIMO antennas to cover NLOS areas and predict the locations of all UEs.

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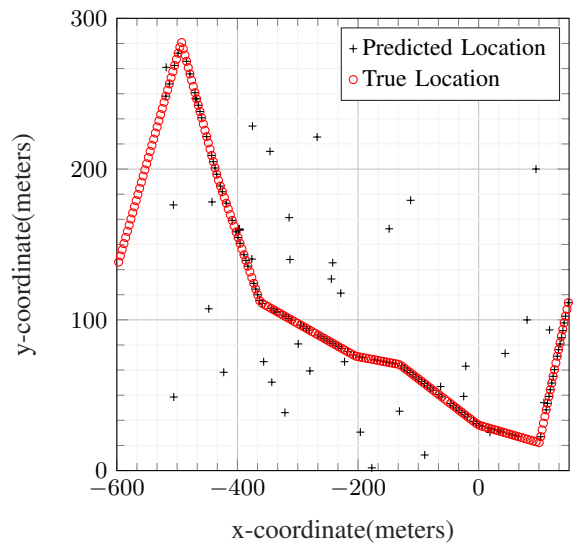

Fig. 2: The predicted locations with respect to the true locations when using DoA, DoD, RSS and ToA.

IV. Conclusion

This paper proposes a method for implementing DNN in localization. The position of a UE can be estimated with great precision using channel information and 25 MPCs. In this study, the DNN is trained using supervised learning approaches, which is achievable with synthetic data. A static case was studied. A more dynamic scenario having foliage , water bodies etc. should be considered for more realistic environment study, which will be addressed in future work.

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