Hybrid Building/Floor Classification and Location Coordinates Regression Using A Single-Input and Multi-Output Deep Neural Network for Large-Scale Indoor Localization Based on Wi-Fi Fingerprinting

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Abstract—In this paper, we propose hybrid building/floor classification and floor-level two-dimensional location coordinates regression using a single-input and multi-output (SIMO) deep neural network (DNN) for large-scale indoor localization based on Wi-Fi fingerprinting. The proposed scheme exploits the different nature of the estimation of building/floor and floor-level location coordinates and uses a different estimation framework for each task with a dedicated output and hidden layers enabled by SIMO DNN architecture. We carry out preliminary evaluation of the performance of the hybrid floor classification and floor-level two-dimensional location coordinates regression using new Wi-Fi crowdsourced fingerprinting datasets provided by Tampere University of Technology (TUT), Finland, covering a single building with five floors. Experimental results demonstrate that the proposed SIMO-DNN-based hybrid classification/regression scheme outperforms existing schemes in terms of both floor detection rate and mean positioning errors.

Index Terms—Indoor localization, Wi-Fi fingerprinting, deep learning, neural networks, classification, regression.

I. INTRODUCTION

Of many localization techniques available nowadays, the location fingerprinting is one of the most popular and promising technologies for indoor localization [1]. Because the location fingerprinting technique does not rely on the access to line-of-sight signal from global navigation satellite systems (GNSSs) and can be implemented based on existing wireless infrastructure (e.g., Wi-Fi APs), it can be readily deployed without installation of new infrastructure or modification of existing one, which is its clear advantage over alternative techniques like triangulation based on time of arrival (TOA) requiring precise synchronization among all transmitters and receivers in the system and non-standard timestamp labeling for the measurement of distances between a target and reference points [2].

In case of Wi-Fi fingerprinting, a vector of pairs of a medium access control (MAC) address and a received signal strength (RSS) from a Wi-Fi access point (AP) measured at a location form its location fingerprint; the location of a user/device then can be estimated by finding the closest match between its RSS measurement and the fingerprints of known locations in a database [3]. One of the major challenges in Wi-Fi fingerprinting is how to deal with the random fluctuation of a signal, the noise from multi-path effects, and the device and position dependency in RSS measurements. Recently the popular deep neural networks (DNNs) have been used in Wi-Fi fingerprinting as well [4]–[9], which can provide attractive solutions due to their less parameter tuning and adaptability to a wider range of conditions with standard architectures and training algorithms. Especially, a single-DNN-based indoor localization system can provide a unique advantage over indoor localization systems based on traditional machine learning techniques that, once trained, it does not need the fingerprint database any longer but carries the necessary information for localization in DNN weights and biases, which could enable a secure and energy-efficient indoor localization exclusively running on mobile devices without exchanging any data with the fingerprint server [8].

When we need to estimate a location in a large building complex like a big shopping mall or a university campus, the scalability of fingerprinting schemes becomes a major issue, too. The current state-of-the-art Wi-Fi fingerprinting techniques adopt a hierarchical approach, where the building, floor, and position (e.g., a label or coordinates) of a location are estimated in a hierarchical and sequential manner using possibly a different algorithm tailored for each task [10]. The application of this hierarchical and sequential approach for multi-building and multi-floor indoor localization to DNN-based schemes, however, may cause scalability issues: As discussed in [8], compared to the traditional techniques as proposed in [10], DNNs for different levels of localization need to be trained separately with either a system-wide dataset (i.e., a DNN for building estimation) or multiple sub-datasets derived from the common dataset (i.e., building-specific datasets for DNNs for floor estimation and building-floor-specific datasets for DNNs for building-floor-level location estimation), which poses significant challenges on the management of location fingerprint databases as well as the training of possibly a large number of DNNs.
To address the scalability issue of DNN-based multi-building and multi-floor indoor localization, the scalable DNN architecture based on multi-label classification [11] shown in Figure 1 was proposed in [8], which can greatly reduce the number of output nodes compared to that of the DNN architecture based on multi-class classification. This DNN architecture also enables customized processing of parts of DNN outputs for building, floor, and location (i.e., the functional blocks on the right in Figure 1) due to the straightforward mapping between building, floor, and location identifiers and its corresponding one-hot-encoded categorical variable.

In this paper, to further exploit the hierarchical nature of multi-building and multi-floor indoor localization, we study the extension of the scalable DNN architecture proposed in [8] based on single-input and multi-output (SIMO) DNN architecture, a special case of more general multi-input and multi-output (MIMO) DNN architecture [12]; this SIMO-DNN-based extension enables hybrid building/floor classification and floor-level two-dimensional location coordinates regression through a dedicated output for each task, which can take into account the different nature of the estimation of building/floor and floor-level coordinates.

The rest of the paper is organized as follows: In Sec. II we revisit the problem of location coordinates estimation in multi-building and multi-floor indoor localization and consider the two options of classification and regression. In Sec. III we propose a new multi-building and multi-floor indoor localization scheme based on SIMO-DNN-based hybrid classification/regression. Sec. IV presents experimental results for the localization performance of the proposed SIMO-DNN-based hybrid classification/regression scheme. Sec. V concludes our work in this paper.

II. LOCATION COORDINATES ESTIMATION IN MULTI-BUILDING AND MULTI-FLOOR INDOOR LOCALIZATION: CLASSIFICATION VS REGRESSION

In [13], the authors present a new crowdsourced Wi-Fi fingerprint database [14] comprised of 4648 fingerprints collected with 21 devices covering the five floors of a six-floor building in Tampere University of Technology, Finland, which is publicly available and hosted in public EU Zenodo repository. Compared to UJIIndoorLoc database [14], i.e., another well-known public fingerprint database covering three buildings with four floors each, the fingerprints of TUT database were collected around a single building, but they provide three-dimensional coordinates (i.e., \((x, y, z)\) of a measurement reference point); the availability of three-dimensional coordinates is indeed a major reason that we use the TUT database in this paper, which motivated us to investigate DNN-based regression of location coordinates.

In [8], the DNN-based multi-building and multi-floor indoor localization is done based on multi-label classification of building, floor and labeled position (i.e., reference points) in the UJIIndoorLoc database training subset. The two-dimensional coordinates of an unknown position is then determined by a weighted average of the coordinates of multiple candidate reference points through the procedure described in Fig. 9 of [8]. Direct regression of location coordinates with DNNs could eliminate such additional procedure.

There is also another reason that we consider a regression-based approach for the TUT database. If we apply classification for the estimation of location as in [8], we need multiple fingerprint samples per label (i.e., reference point) to train DNNs. This is the case for the UJIIndoorLoc database training subset, where there are about 21 fingerprint samples per reference point in average (≈19674 samples: 933 reference points). Because the fingerprints in the TUT database are not collected at fixed reference points (e.g., office, lab, and corridor) or grid points but at any points inside and outside the building, however, there are few fingerprint samples per measurement point; for its training subset of 697 fingerprint samples, there are 694 unique locations, which results in 1004 samples per reference point in average. Therefore, regression is the only viable option for floor-level location coordinates estimation with the TUT database.

Regarding floor estimation, we consider two options, i.e., pure regression of three-dimensional location coordinates and hybrid floor classification and regression of two-dimensional location coordinates: If we treat the \(z\) coordinate of a location as exactly as the \(x\) and \(y\) coordinates, we can apply pure regression for three-dimensional coordinates. If we treat the \(z\) coordinate as a label (i.e., multiples of 3.7 — 0, 3.7, 7.4, 11.1, 14.8 — for five floors), on the other hand, we can apply classification for floor estimation, while \((x, y)\)
coordinates estimation is still done by usual regression. Compared to the pure regression of three-dimensional location coordinates, we can better exploit the hierarchical nature of multi-building and multi-floor indoor localization with the hybrid classification/regression by separate processing of the information at different levels.

These considerations lead us to a SIMO DNN architecture described in Sec. III, which enables the hybrid classification/regression approach.

### III. SIMO DNN FOR HYBRID CLASSIFICATION AND REGRESSION

Given the availability of three-dimensional coordinates of reference points in the TUT database, one can come up with an indoor localization scheme based on the DNN-based coordinates regression shown in Fig. 2 which serves as a reference scheme in this paper. This single-input and single-output (SISO) DNN-based three-dimensional coordinates regression scheme, however, treats all three coordinates equal and thereby cannot take into account the discrete nature of \( z \) coordinate (i.e., multiples of 3.7) and its relation to the floor estimation, which should be given priority over the other two coordinates.

As shown in Fig. 3 on the other hand, the SIMO DNN architecture enables the use of a different estimation framework for a different sub-problem; with a separate output and hidden layers dedicated for a sub-problem, we can use different activation and loss functions optimized for the choice of estimation framework. For example, we can use `softmax` activation function and `categorical crossentropy` loss function for multi-class classification of floor at the floor output, while we can use `linear` activation function and `mean squared error (MSE)` loss function for regression of location coordinates at the location output.

Note that in the proposed SIMO DNN architecture, the SAE of the single-DNN architecture proposed in [3] (also shown in [1]) is replaced by the stacked denoising autoencoder (SDAE) based on the results in [15], where the authors argue that `denoising autoencoder pretraining` provides better classification performance than `ordinary autoencoder pretraining` because

The definitions of SISO, SIMO, and MIMO DNN architectures are implementation-oriented rather than mathematical; even with SISO, we can have multiple input values (i.e., a vector-valued input), which, however, are grouped together with a common loss function and a loss weight.

The denoising criterion as a tractable unsupervised objective enables DNNs to learn more useful higher-level representations. Our own experimental investigation also confirms this claim.

### IV. EXPERIMENTAL RESULTS

To evaluate the localization performance of the proposed SIMO-DNN-based hybrid classification/regression scheme, we carry out experiments using the new TUT Wi-Fi fingerprinting database [13], covering a single building with five floors. Both SISO (reference) and SIMO (proposed) DNN models are implemented based on Keras [16] and TensorFlow [17].

We use `EarlyStopping` together with `ModelCheckpoint` callbacks of Keras to save the best weights and biases during the training phase and use them for the performance evaluation with a test dataset. Each simulation run is repeated twenty times with different random number seeds to calculate a 95% confidence interval. Tables I and II summarizes DNN parameter values, which are chosen experimentally and used throughout the experiments.

Fig. 4 shows the effect of coordinates loss weight on the localization performance of the proposed SIMO-DNN-based hybrid classification/regression scheme, where we plot mean two-dimensional positions error, mean three-dimensional positioning error, and floor detection rate, all with 95% confidence intervals. For a comparison, we also show the localization performance of the SISO-based three-dimensional coordinates regression of three horizontal lines (i.e., the dash-dotted line in the middle for a mean value and the two dash lines for a 95% confidence interval).

The mean two-dimensional and three-dimensional positioning errors shown in Fig. 4 (a) and (b) indicate that the proposed SIMO-DNN-based hybrid classification/regression scheme outperforms the reference SISO-DNN-based regression scheme for a wide range of coordinates loss weight; in case of floor detection rate shown in Fig. 4 (c), the proposed scheme provides better performance than the reference one (i.e., around 1% higher floor detection rate) irrespective of the coordinates loss weight. The detailed investigation of the results shows that coordinates loss weight of 0.8 (with floor loss weight of 1.0) provides the best overall performance. Also, from the overall results shown in Fig. 4 we observe
**TABLE I**
SIMO DNN Parameter Values for Hybrid Classification/Regression.

| DNN Parameter                             | Value                                      |
|-------------------------------------------|--------------------------------------------|
| Fraction of training data used as validation data | 0.2                                        |
| Number of Epochs\(^1\)               | 100                                        |
| Batch Size                                | 64                                         |
| Optimizer                                  | Nesterov-accelerated Adaptive Moment Estimation (NADAM) \(^{[18]}\) |
| SDAE Hidden Layers                        | 1024-1024-1024                             |
| SDAE Activation                           | Sigmoid                                   |
| SDAE Corruption Level                     | 0.1                                       |
| SDAE Loss                                  | Mean Squared Error (MSE)                   |
| Common Hidden Layer                       | 1024                                      |
| Common Hidden Layer Activation             | Rectified Linear (ReLU)                    |
| Common Hidden Layer Dropout Rate           | 0.25                                      |
| Floor Classifier Hidden Layer              | 256                                        |
| Floor Classifier Hidden Layer Activation   | RelU                                      |
| Floor Classifier Hidden Layer Dropout Rate | 0.25                                      |
| Floor Classifier Output Layer Activation   | Softmax                                   |
| Floor Classifier Loss                      | Categorical Crossentropy                   |
| Coordinates Regressor Hidden Layer        | 256                                        |
| Coordinates Regressor Hidden Layer Activa- | ReLU                                       |
| tion                                | Coordinates Regressor Hidden Layer Dropout Rate | 0.25 |
| Coordinates Regressor Output Layer Activa- | Linear                                    |
| tion                                | Coordinates Regressor Loss                 | MSE                                        |

\(^1\) With Keras EarlyStopping (min_delta=0 and patience=10) and ModelCheckpoint callbacks.

**TABLE II**
SISO DNN Parameter Values for Three-Dimensional Coordinates Regression.

| DNN Parameter                             | Value                                      |
|-------------------------------------------|--------------------------------------------|
| Fraction of training data used as validation data | 0.2                                        |
| Number of Epochs\(^1\)               | 100                                        |
| Batch Size                                | 64                                         |
| Optimizer                                  | NADAM \(^{[18]}\)                          |
| SDAE Hidden Layers                        | 1024-1024-1024                             |
| SDAE Activation                           | Sigmoid                                   |
| SDAE Corruption Level                     | 0.1                                       |
| SDAE Loss                                  | MSE                                       |
| Common Hidden Layer                       | 1024                                      |
| Hidden Layer                              | 1024                                      |
| Hidden Layer Activation                   | ReLU                                      |
| Hidden Layer Dropout Rate                 | 0.25                                      |
| Output Layer Activation                   | Linear                                    |
| Coordinates Regressor Loss                | MSE                                       |

\(^1\) With Keras EarlyStopping (min_delta=0 and patience=10) and ModelCheckpoint callbacks.

Fig. 4. Effect of coordinates loss weight (with fixed floor loss weight of 1.0) on the localization performance of SIMO-DNN-based hybrid classification/regression: (a) Mean two-dimensional positioning error [m], (b) mean three-dimensional positioning error [m], and (c) floor detection rate [%].
that the use of proper estimation framework for a given task enabled by the SIMO DNN architecture is more important than the loss weight control of multiple outputs.

Table III compares the localization performance of the proposed and reference schemes with the best results from the benchmark positioning results in [13]. Even though the TUT dataset division is more challenging than other available Wi-Fi datasets, by having only 15% of samples for training/reference, compared to 85% of samples for evaluation, the proposed SIMO-DNN-based hybrid classification/regression scheme outperforms the best algorithms from the benchmark in [13] in all three categories, which is remarkable considering that DNN-based schemes require lots of training data compared to traditional machine learning techniques.

Note that the results presented in this section are preliminary and only with the TUT database; the current work is focused on the feasibility of the proposed SIMO-DNN-based hybrid classification/regression scheme in comparison with the SISO-DNN-based pure regression scheme and the state-of-the-art Wi-Fi fingerprinting techniques.

V. CONCLUSIONS

In this paper we have proposed SIMO-DNN-based hybrid building/floor classification and floor-level two-dimensional location coordinates regression for large-scale indoor localization based on Wi-Fi fingerprinting. This hybrid approach for indoor localization enabled by SIMO DNN architecture can better exploit the hierarchical and different nature of the estimation of building/floor and floor-level location coordinates.

The experimental results with the TUT database demonstrate the advantages of the proposed scheme, which can provide the best overall performance in terms of mean two-dimensional and three-dimensional positioning errors and floor detection rate in comparison to the best algorithms from the benchmark in [13] as well as the reference scheme based on SISO-DNN-based three-dimensional coordinates regression.

The results presented in this paper suggest that the proper use of estimation frameworks tailored for given sub-problems (i.e., multi-class classification for building/floor estimation and regression for floor-level two-dimensional coordinates estimation) enabled by SIMO DNN architecture can address the challenging aspects of the TUT database, including just one sample per reference point (compared to tens or hundreds in other databases) and the unusual split ratio between training/reference and evaluation samples (i.e., 15:75).

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| Algorithm                                      | Mean 2D Error [m] | Mean 3D Error [m] | Floor Detection [%] | Notes                  |
|------------------------------------------------|-------------------|-------------------|----------------------|------------------------|
| SIMO-DNN-Based Hybrid Classification/Regression[^1] | 7.46[^2]          | 7.53[^2]          | 94.5[^3]             | Proposed scheme.       |
| SISO-DNN-Based 3D Regression                   | 7.88[^2]          | 7.94[^2]          | 94.2[^3]             | Reference scheme.      |
| RSS Clustering (Affinity Propagation) [19]     | 8.09              | 8.70              | 90.81                | From [13]              |
| UJI kNN Algorithm [20]                         | 8.65              | 8.92              | 92.99                | From [13]              |

[^1] With floor loss weight=1.0 and coordinates loss weight=0.8.
[^2] Minimum value from 20 runs.
[^3] Maximum value from 20 runs.
[^4] With data=powed, dist=sorensen, N_{nn}=1, Not_{head}=-103 [13].