An adaptive statistical learning model for fingerprinting based WIPS

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Objectives

- Develop an approach to construct/update the radio map (RM) which consists of the reference points (RPs) and corresponding received signal strengths (RSS) from the available WLAN/WiFi access points for fingerprinting based WIPS (FWIPS) efficiently, i.e. involving little investment of time, money and labor.
- Investigate the benefit of integrating RM construction/update with positioning/trajectory tracking.
- Establish a testbed for experimental demonstration of the performance of the newly developed algorithms as compared to existing solutions.

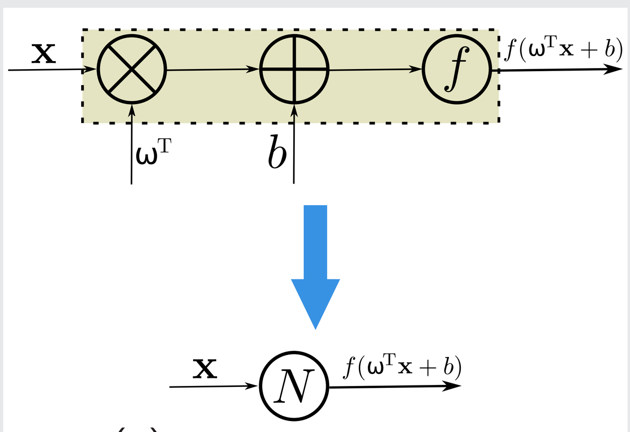
The First Trial

The first trial is employing backpropagation neural network (BPNN) to learn the mutual mapping relationship between RP coordinates and RSS vectors for both RM construction and positioning (This is mainly from the paper to be appeared on UPINLBS 2016). The main contributions are:

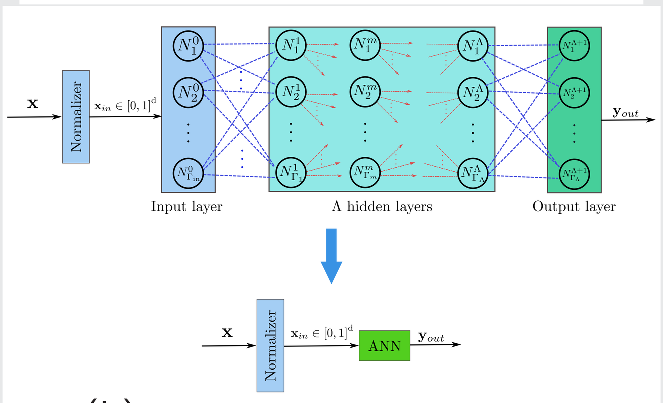
- Apply BPNN to indoor localization (BPNN based localization, BPNN-LA), and fast radio map construction starting from a sparse training radio map (TRM) (BPNN based radio map construction, BPNNRM).
- Investigate the performance of the proposed scenario compared to two popular fingerprinting localization algorithms (FLAs), k nearest neighbors (kNN) and weighted kNN (WkNN).
- Analyze the impact of various choices of BPNN design parameters via numerical simulations and derive proposals regarding these choices.

BPNN

- Node: A node is the elementary unit of an artificial neural network (ANN). The outputs of the other nodes of the same layer—the input of the subsequent layer or the output of the ANN.
- Layers: (i) The input layer transforms the general input into the space which is determined by the number of nodes of this layer. (ii) The required number of hidden layers depends on the application, especially on the non-linearity of the relation between input and output.
- Error propagation:The purpose of the training is to determine the weights and biases such that the error is minimized using the training data set while the activation functions, number of hidden layers and numbers of nodes within each layer are fixed.



(a) A single node of ANN



(b) The basic structure of ANN

Figure 1: Schematic view of a single node and the layered structure of a BPNN

The Proposed Algorithms

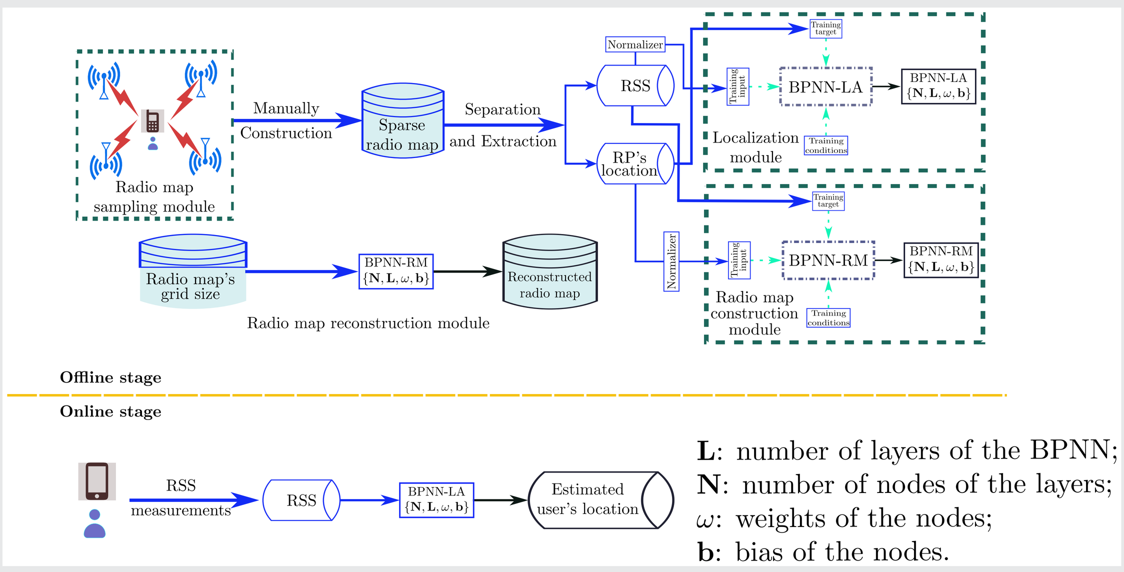


Figure 2: Systematic view of the proposed algorithms

- RM generator module: At given RPs a surveyor uses the sampling device (e.g. a mobile phone) to collect the RSS from all available APs within the RoI.
- BPNN-RM: The normalized coordinates are the input to the trained BPNN-RM which is learned from the normalized RP coordinates and corresponding RSS via BPNN.
- BPNN-LA: The normalized RSS vectors and the corresponding RP locations are the training input and training target of BPNN and trained BPNN maps the newly measured RSS to the coordinates space.

Testbed

- Testbed: There are 8 APs in the experimental area, which are attached stably to the wall at a height of 2m from the floor in the 10^{th} floor of the 2A building at Harbin Institute of Technology.
- RM: RSS were recorded at points arranged in a regular grid of $0.5 \times 0.5m^2$ yielding an original RM (ORM) with a grid size of $0.25m^2$.

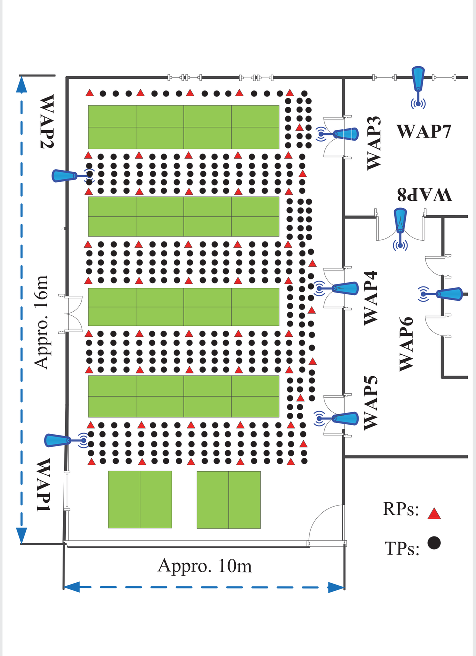


Figure 3: Indication of testbed

Results: BPNNLA

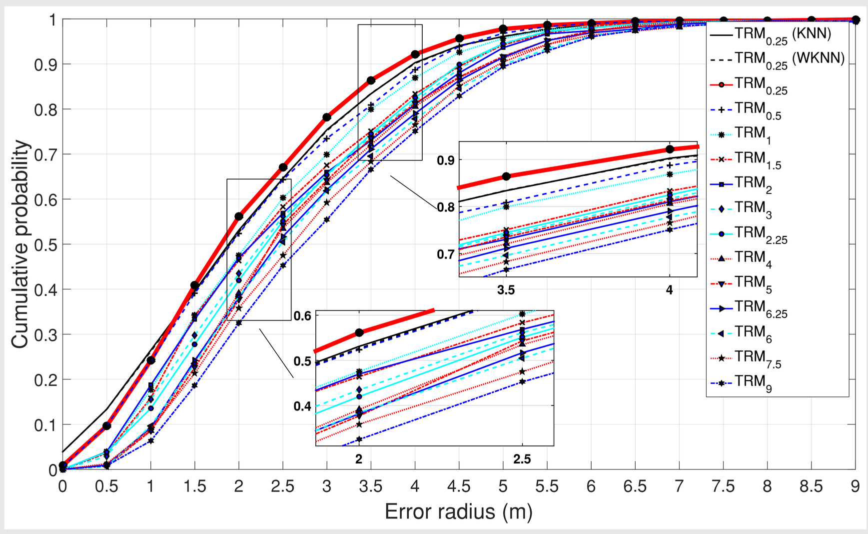


Figure 4: Cumulative probability of positioning error for BPNN-LA

With $\mathrm{TRM}_{0.25}$, i.e. a training RM with grid size of 0.25 m^2, BPNN-LA outperforms the other solutions and is even better than kNN and WkNN with the same TRM. For BPNN-LA with 1 hidden layer about 68% of the errors are below $2.5\mathrm{m}$. Over 99% of the estimated locations are within an error radius of $8\mathrm{m}$ which is accurate enough for room level positioning.

Results: BPNNRM

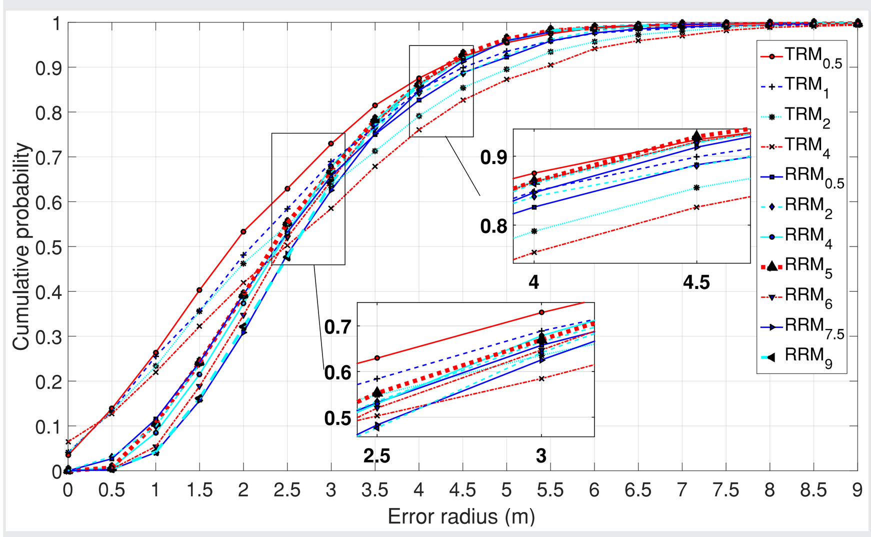


Figure 5: Cumulative error probability for kNN with RRM

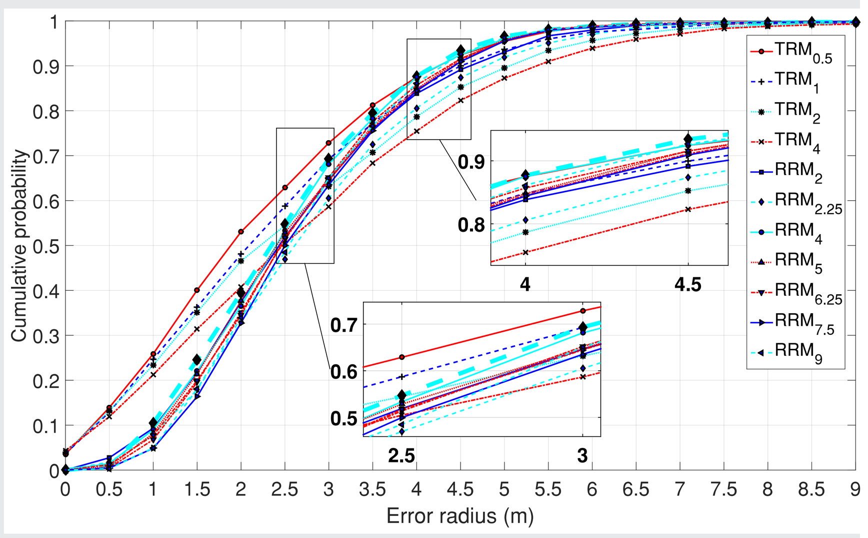


Figure 6: Cumulative error probability for WkNN with RRM

As shown in the figure, we find that: (i) The positioning accuracy of both kNN and WkNN using the selected RRMs are higher than using the respective TRM with equal grid size when considering errors larger than $2.5\,\mathrm{m}$. (ii) The RRMs yielding the best performance with kNN and WkNN are RRM_5 and $\mathrm{RRM}_{2.25}$. 92% and 95% of the errors are smaller than $4.5\,\mathrm{m}$ when using them. (iii) the workload for creating the radio map by almost 90% when collecting only the data required for TRM_4 instead of $\mathrm{TRM}_{0.5}$ and still obtaining better results by converting the TRM_4 into a RRM with a grid size of $2.25\,\mathrm{m}^2$.

Conclusion

- BPNN-LA with 1 hidden layer (HL1) outperforms kNN, WkNN and BPNN with multiple hidden layers in terms of the mean error radius.
- 90% of the positioning errors are within $4m$ using HL1 trained by the $0.25m^2$ grid size radio map.
- As for the reduction of the workload required to build the RM, BPNNRM reduces it by almost 90% since it allows using TRM_4 instead of $TRM_{0.5}$ while still obtaining equal or even slightly better performance.

Future Plan

- Establish a fingerprinting based WIPS in the HIL building of ETH Zurich mainly in the D floor and including at least parts of the C and E floors and sample the fingerprinting data (e.g., RSS, magnetic field and air pressure) using mobile device.
- Investigate and apply statistical learning theory to achieve simultaneous RM construction/update, positioning and trajectory tracking.