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I see you: On Neural Networks for Indoor Geolocation

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Abstract. We propose a new passive system for indoor localization of mobile nodes. After the setup, our system only relies on arbitrary wireless communication from the nodes, whereby neither the mobile nodes nor the communication needs to be under our control. The presented system is composed of three Artificial Neural Networks (ANN) using a radiomap approach and the Received Signal Strength (RSS) for localization. A Probabilistic Neural Network (PNN) decides between two Generalized Regression Neural Networks (GRNN) that process the actual RSS measurement. In practical experiments we achieve a mean location error of 0.58 m which is 22.64% better than a single GRNN approach in our setup.

Keywords: localization, ANN, GRNN, RBFN, GRFBN, PNN

1 Introduction

Precise localization of mobile devices is an important goal for location based services. Many companies, e. g. Google and Apple, already provide solutions for location based services, both for indoor and outdoor localization. Outdoor localization is commonly realized with GPS, the de facto standard technology for localization. However, since GPS signals are reflected and shadowed by walls it can not be used in indoor scenarios.

IEEE 802.11 wireless lan (WLAN), Zigbee or Bluetooth (e. g. Apple iBeacon) are alternatives to GPS, when locating a mobile target inside a building. Due to the high availability of WLAN in many buildings, a WLAN based positioning system can be established with relatively low costs, using existing communication infrastructure. Exploiting parameters of WLAN signals, such as Received Signal Strength (RSS) or Time of Arrival (ToA), allows estimating the position of a mobile target.

Indoor localization is mostly done with a fingerprinting-based approach. A pioneer work in locating a mobile device using RSS-Fingerprints is Microsoft RADAR [1]. The fingerprints are stored in a database called *radiomap*. RADAR achieves an accuracy of 2 m to 3 m using empirical fingerprints and k-nearest-neighbor-algorithm (KNN) to determine the location.

Battiti, Le, and Villani [2] use a neural network instead of KNN for location-determination. Neural networks are well-suited for localization, since you can consider the location-problem as a function approximation. They report an average location error of 3 m, which can be reduced to 1.5 m by increasing the number of training samples. The applied neural network was a multilayer perceptron (MLP) using one-step secant training method.

Apart from MLP a second network architecture is often used for localization. This is the Radial Basis Function Network (RBFN) and the Generalized Regression Neural Network (GRNN) [7], which is a special RBFN. Several authors studied whether MLP or RBFN is better suited for localization. Comparisons regarding the achieved accuracy with MLP and GRNN are made in [11, 6, 9]. In most cases GRNN performs slightly better than the MLP. For example Outemzabet and Nerguizian [6] report a median location error of 3.56 m and 2.45 m for the MLP and GRNN, respectively.

To the best of our knowledge, all relevant studies using RBFN (GRNN) for indoor-localization rely on MATLABs Neural Network Toolbox [3]. In this paper we propose an own implementation of GRNN with several optimizations for indoor localization that outperforms all previous research results in terms of accuracy.

According to Specht [7] RBFNs are superior to GRNNs when training data is presumed to be accurate i.e. there is very low noise. A RBFN calculates the weights to perfectly fit the training data, which is pointless for very noisy training sets. Depending on the level of noise RBFN or GRNN will achieve better results. Practical measurements (section 2) were performed to analyze which network is best suited for indoor localization with IEEE 802.11 WLAN.

The organization of the paper is as follows: Section 2 describes our experiments for determining the ANN with the highest location accuracy. Section 3 presents a system with higher accuracy than the previous works and section 4 concludes the paper.

2 Practical geolocation results

In this section we analyze the practical relevance of ANNs for geolocation by taking practical measurements into account. Our test setup consists of an Atheros AR9287 based Access Point using hostapd. The AP is placed in the center of eight monitor stations that use packet sniffers to extract the RSS from the IEEE 802.11g WLAN (2.4 GHz) signals. Our measurement setup is shown in fig. 1 where M_1 to M_8 identify the monitor stations and the black dots the calibration points used for radiomap creation.

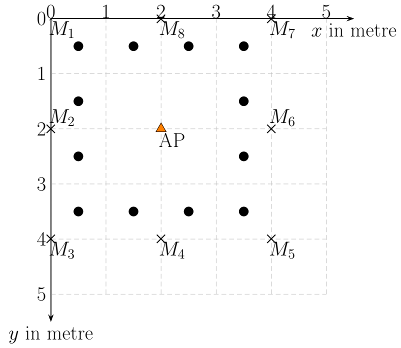


Fig. 1: Measurement setup

In order to keep hardware dependent impact on measurements as low as possible, all monitor stations use Atheros AR9271 wireless networks adapters to collect RSS values. In the online phase, RSS information were gained from observing IEEE 802.11 ACK frames that occur whenever a data frame arrives at the target. For the purpose of reducing the experiments duration, we induced the target to send ACK frames in an interval of 1 ms until 1000 RSS values were collected. A Google Nexus 4 with Android 4.4.2 was used as mobile target.

2.1 Practical measurements

Three neural networks (GRNN, RBFN and GRBFN) were examined for the localization of the mobile target. The three networks were implemented in Python using the parameters presented in table 1.

Table 1: Parameters of the three examined Neural Networks

Network	Parameters
GRNN	• Radius $\sigma_G = 8.59$ • 12 hidden neurons
RBFN	• Radius $\sigma_R = 18.99$ • 12 hidden neurons
GRBFN	• Radiusvector $\boldsymbol{\sigma} = (18.99, \ldots, 18.98)$ with 8 elements • 8 hidden neurons • 20 training iterations for $\boldsymbol{\sigma}$ • 20 training iterations for output weights

For determining the radius σ of a GRNN/RBFN, Haykin [4, p. 299] proposes the heuristic $\sigma_{est} = \frac{d_{max}}{2 \cdot N}$, where d_{max} is the maximum (euclidean) distance of training vectors and N, the number of training samples. In order to achieve more precise results, this formula is modified to take the number of monitor stations into account. The radius σ_G of the GRNN is calculated by

$$\sigma_G = \sqrt[6]{m} \cdot \sigma_{est} = \frac{d_{max} \cdot \sqrt[6]{m}}{2 \cdot N} \tag{1}$$

with m specifying the number of monitor stations i.e. the dimension of the input vectors. For the radius σ_R of the RBFN the heuristic

$$\sigma_R = \sqrt{m} \cdot \sigma_{est} = \frac{d_{max} \cdot \sqrt{m}}{2 \cdot N} \tag{2}$$

is used. Both formulas σ_G and σ_R were determined and proofed heuristically. The GRBFN vector $\boldsymbol{\sigma}$ is based on σ_R.

2.2 Analysis of the results

The measurement results (table 2) were processed at 48 locations and show that the GRNN performs better than RBFN and GRBFN algorithms in terms of mean location error (error defined by euclidean distance) and median error.

In terms of the 75% percentage CDF (Cumulative Distribution Function) the RBFN performs slighty better than the GRNN algorithm. However, the GRNN achieved best results in our test setup which can also be verified with the CDF curve of the location error (fig. 3a).

Since the GRNN algorithm outperforms both other algorithms, we use it as basis for further optimizations in the next section.

3 Optimizing the generalized regression neural network

In this section we propose a locating system consisting of two Generalized Regression Neural Networks (GRNN) that further improves the previous results.

To enhance the location accuracy the function approximation problem of f was split into an interpolation and extrapolation problem. Two GRNNs with different radii were used, performing interpolation and extrapolation, respectively. The first network, $GRNN_0$, estimates all locations *inside* the radiomap i.e. it performs function **interpolation**. The second network, $GRNN_1$, estimates all locations *outside* the radiomap, i.e. it performs a function **extrapolation**.

In order to use this approach, an input vector $\boldsymbol{rss}$ of RSS values must be assigned to either θ_0 (inside radiomap) or θ_1 (outside radiomap). This classification was performed by a *Probabilistic Neural Network*.

Probabilistic Neural Networks (PNN) [8] are well suited for classification as they are robust to noise [5] and get along with a small amount of training data [10]. For these reasons PNNs are attractive for the decision between inter- and extrapolation in our localization system.

We employ a PNN with $\sigma_P = 3.10$ which was heuristically found. The PNN, trained with the radiomap and ten additional locations, classifies 47/48 possible locations correctly. A graphical illustration of our complete system and its radii is shown in fig. 2.

Our proposed system takes the same measurement data as used in the previous setup in section 2.1.

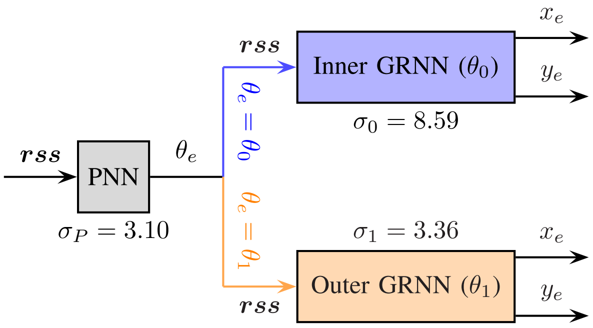
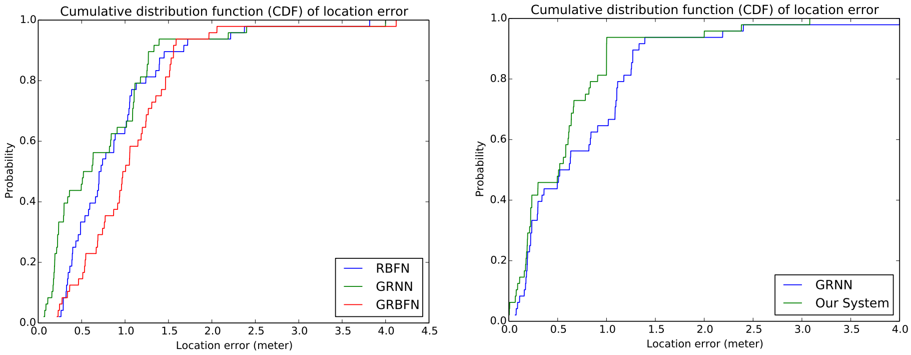


Fig. 2: Our proposed system

Results (fig. 3b and table 2) show that our system beats the GRNN in terms of mean location error with a system gain of 22.64%.



(a) For GRNN, RBFN and GRBFN

(b) For GRNN and our system

Fig. 3: CDF of location estimate errors

Table 2: Positioning Errors (m)

Technique	Mean	Median	CDF (75%)
RBFN	0.8936	0.7127	1.0611
GRBFN	0.9511	0.8089	1.1944
GRNN	0.7557	0.5704	1.1051
Our System	0.5845	0.5146	0.7928
System Gain resp. GRNN	22.6455%	9.7694%	28.2632%

4 Conclusion

We proposed a new system for indoor localization. The system consists of two GRNNs, splitting the function approximation problem into an interpolation and extrapolation problem and one PNN for the decision between both GRNNs. We decided to go with the GRNN as primitive, because it outperforms RBFN and GRBFN in practical measurements (section 2) in terms of location accuracy.

Our system achieves a mean location error of 0.58 m which is an enhancement of 22.64% compared to the single GRNN approach. Compared to other research results for indoor localization with neural networks, our system increases the accuracy by even 1 m to 2 m. It should be noted, that our setup was made under ideal conditions, while measurements in related work were taken in office buildings. We expect, that our system will perform less accurate in similar environments because of obstacles (e. g. walls) and moving persons.

Our system creates two classes (inside and outside the radiomap). In a more general approach you could use more classes with one GRNN assigned to each class. First tests with four classes resulted in an accuracy of 0.66 m. This is still better than the single GRNN approach but slighty worse than the accuracy achieved by our system with two classes. Future work has to focus on finding reasonable numbers of classes and the geometrical shape of the classes (e. g.

rectangular, triangular). The choice of GRNN as our main system component strongly depends on noise of the measurement data. If there is no noise the RBFN outperforms the GRNN by 0.3 m in terms of accuracy which can be learned from a simulation. Future work is the determination of how small the standard deviation of the noise must be, so that a RBFN becomes more attractive than a GRNN. Since you can lower the effect of noise by taking the mean of more measurements at one location, this is not only a theoretical question.

The accuracy of our system depends on the chosen radii for both GRNNs. Future work will reveal, whether our heuristics for the radii (eqs. (1) and (2)) can be applied to other setups. Another optimization would be to exploit different signal parameters besides RSS, e.g. Time of Arrival.

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