Device-Free User Localization Utilizing Artificial Neural Networks and Passive RFID

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Abstract – **User localization information is an important data source for ubiquitous assistance in smart environments. This paper proposes a device-free passive user localization approach based on room-equipped passive RFID instead of battery powered hardware. Based on this approach recent work tried to formulate physical model based localization algorithms. These approaches suffer from their inability of integrating environmental changes like the deployment under moving experimental conditions. On the other hand most model based approaches have a certain trade-off between a high localization precision and computational complexity. In this work we try to formulate a training based approach to the problems with the help of artificial neural networks. Special representatives like multi-layered perceptrons are applied to a wide range of problems where it is difficult to model the underlying physical condition completely.**

We present a perceptron implementation for the purpose of user localization and conduct first results with different model parameters and functions.

Keywords: Radio Frequency Identification, Navigation, Radio Navigation, Artificial Neural Networks, Signal Processing

I. Introduction

The position of users is an important parameter for location aware systems and ubiquitous computing. Superimposed intention recognition systems rely on location-aware data for reliable smart assistance. Typically users in intelligent environments want to act free and spontaneous. Active localization systems operate by implicit localization of user attached hardware. This does not meet the requirements of free and spontaneous collaboration and has two key disadvantages: The deployment of user hardware needs a huge amount of maintenance work if changing user groups needs to be localized. Second the user-mounted hardware needs to be powered independently, which leads to the need for battery power and resulting battery maintenance effort. In our research group a new device-free passive localization approach (DFL) is explored. Battery powered radio hardware can be replaced by completely passive *Radio Frequency Identification* transponders (pRFID) without the need of additional power sources. The only powered component is the RFID reader infrastructure with a few active antennas. This has two benefits: The transponders can be placed very easily within the room. It is possible to place those tags for instance under the carpet or beneath the wallpaper. The density of nodes and consequently the localization resolution can be adapted very easily. The second benefit is the low-cost character of passive RFID hardware: transponders can be purchased for ~ 0.2 €. Additionally there aren´t any maintenance costs.

Up to now the developed localization techniques are model-based approaches and statistical estimators. Adapting physical models on a RF-problem dealing with multipath fading effects is very difficult and needs to make arbitrary assumptions about real world phenomena like signal distributions and error models. Statistical estimators generally show a trade-off between computational complexity and achievable precision.

Training-based approaches are subject to research in the localization area. Using e.g. artificial neural networks (ANN) may be utilized without making any model related or distributional assumptions. In this work we try to evaluate variations of ANNs to get an idea about statistical interrelations between the physical measurement setup and the sensor data by machine learning. This could give us the chance to synthesize an explicit model from the learned implicit model. Hence the problem of localizing users by utilizing training-based machine learning methods is subject of this work.

The paper is structured as follows. After an overview about existing technologies and approaches, in chapter 3 the methodology is explained which we used for our problem. Chapter 4 contains our simulation test bed, followed by our results. At the end we draw conclusions and give a short overview about future work.

II. State of the Art

This chapter gives a short overview about the underlying approaches for this paper. The key techniques are device-free systems, the pRFID based approach and already existing studies about multi-layered perceptrons for localization purposes.

A. Device-free Localization (DFL)

There are only a few research groups working in the field of device-free or also called passive localization. Estimating the position of users without user-attached hardware seems to be a

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harder problem, due to several interferences and lower possible accuracies. The following sensor technologies are usable for DFL:

- Cameras (optical, thermal, infrared)
- Groundsensors (Pressure, Capacity)
- Acoustic, Vibration and Ultrasound
- Radio Frequency

Cameras have the disadvantage of limited view angles and they are sensible to blocking objects in front of them. They need relatively stable light conditions and have the problem of privacy in public areas. Acoustic sensors (i.e. ultrasound, bodysound etc.) generally suffer from interferences on equal frequencies. An approach already utilizing ground sensors as available product on the market is the SensFloor® from FutureShape[1], utilizing footprint capacity changes measured by room equipped ground plates. There is a number of approaches utilizing RF for user localization, but only a small number operating in a device-free manner. One is proposed i.e. by Wilson et al. [2], [3] utilizing wireless node (WSN) communication for a scatterer based user localization within an imaging based algorithm. Zhang et al. [4], [5] also propose a WSN approach with nodes placed on the ground and on the ceiling of the room. Furthermore an often proposed RF technology is UWB, because high reachable accuracies [6]. A system often benchmarked is the Ubisense® system by Ubisense Ltd.[7], which is operating device-based. Transponder tagged users are localized via UWB pulse time measurements.

B. PRFID DFL

Device-free Localization utilizing passive RFID transponders was subject of research in recent years. Lieckfeldt et al. [8], [9] first worked out the effect of a scattering user on a ground deployed passive RFID field, cp. Fig 1. The authors propose a physical model depicting the effect of the relative user position on the measureable signal strength. They propose estimators for user localization based on i.e. maximum likelihood (MLE) and geometric methods, i.e. nearest intersection points (CNIP). While the estimation based algorithms suffer from computational complexity, the geometric approaches have a very low accuracy.

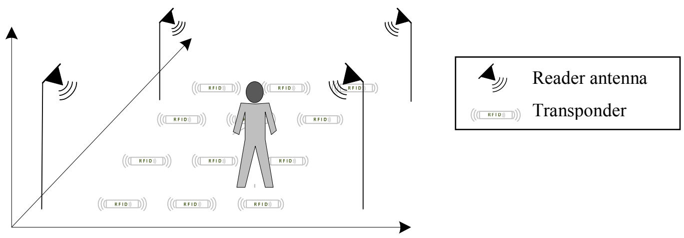

Fig. 1: Basic pRFID scenario

Hence in [10] a combined approach which applies tomographic imaging algorithms onto a passive RFID system is proposed. Using this approach a high accuracy with low computational complexity at runtime is reachable. While a person is moving within an area surrounded by passive RFID transponders, the received signal strength values of the single radio links are influenced. Based on that data a tomographic image of the localization area can be calculated, its structure gives information about the location and the movement of a scattering object, cp. Fig. 2.

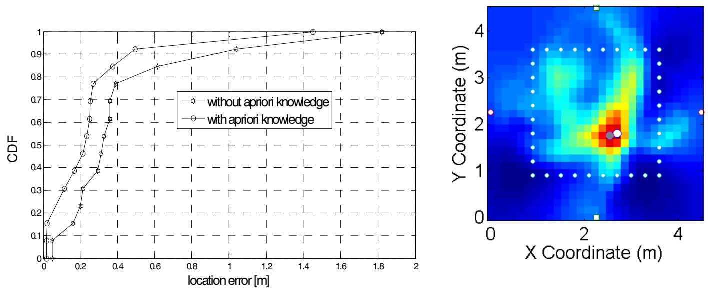

Fig.2: Example Image and results of pRFID tomographic imaging

C. Localization using multi-layered perceptrons (MLP)

There is a number of existing publications dealing with device based localization utilizing MLP based approaches. Ahmad et al.[11] i.e. apply a Multi-Layer Perceptron on a Received Signal Strength (RSS) based indoor WLAN localization approach. The authors employ multiple perceptrons for merging data from different access point combinations. Different transfer and training functions are evaluated. The results show that average errors below 0.2 m are possible. Ergut et al. [12] provide a device-free approach based on *Ultra wideband* (UWB) technology and TDOA measurements. The authors also choose the MLP for training-based localization and backpropagation for the network training. A comparison between Cramer-Rao bound (CR), least squares estimation (LSE) and neural network approach shows that the training based method performs better than the LSE with a sufficient number of input sensor data. With rising input information a performance like the CR can be archieved. Shareef et al. [13] qualitatively compare three different neural network with respect to their ability of solving device based localization problems in wireless sensor networks. The authors have done experiments with a 9×2 two layer MLP, with hyperbolic tangent sigmoid activation function in the first and linear activation in the second layer. The MLP achieves a localization error of 0.057 m per estimate and was only beaten by a radial basis function neural network (RBF).

III. METHODOLOGY

A. Experimental Data Creation

Lieckfeldt et al. [14] propose a physical model to describe the influence of human body interaction with passive RFID communication. The authors associate the change of the received signal strength with the path difference d_{exc} between two radio signals travelling on a LOS path directly from transponder to the reader and on a NLOS path reflected by an scatterer. This can mathematically be described as:

$$\Delta E(d_{exc}) = A d_{exc}^{B} \cos\left(\frac{2\pi}{\lambda} d_{exc} + \phi_{refl}\right) [14]$$

where ΔE is the estimated RSSI change, λ is the wave length the system is operating on and $\square_{\text{refl}}$ is the phase shift. The parameter bundle A,B, λ and $\square_{\text{refl}}$ is subject to the experimental environment due to multipath fading effects. Therefore the model needs to be re-adjusted to each experimental setup.

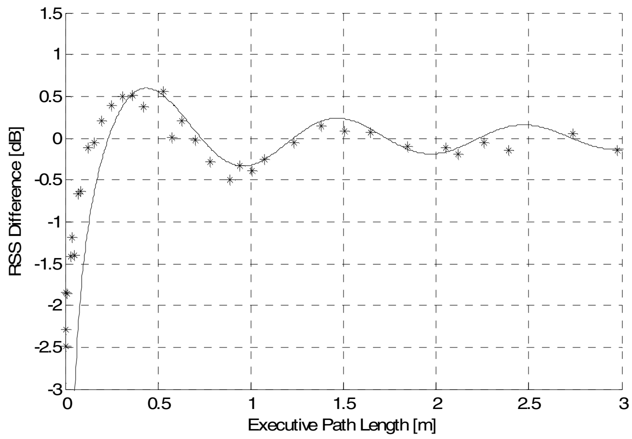

Fig. 2 Theoretical model regression and experimental data points from a 69 transponder indoor scenario

The parameter needs has to be re-calibrated very carefully for every new deployment. To get a parameter set for our setup, where 69 passive transponders are placed on the ground of an $5 \times 8\ m$ room, shown in figure 3.

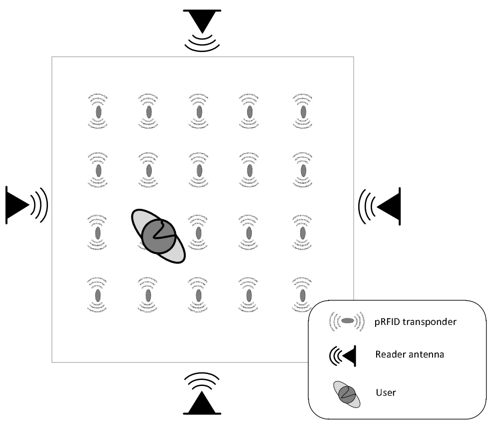

Fig. 3 Sample indoor scenario

Due to the linear polarization of the 4 RFID reader antennas we had to find a transponder orientation which leads to best read results. If the tags are fitted to the antenna polarization direction the antennas have 6 dB gain. Thus, we decided to double every transponder with an orthogonally placed second one. Furthermore we summarize the measurements of every adjacent transponder pair to one available radio beacon.

For fitting the data from our measurements to the described physical model we used a fitting script working in a linear least-squares sense, leading to the following parameter structure, displayed in table 1. The theoretical model regression and our experimental data are shown in figure 2.

Parameter	Fitted value
A	.2
B	-1.1
μ	.3454
ϕ_{refl}	3.4

Table. 1: Physical model parameters

B. Perceptron design

For localization purposes we propose a three layered neural network as part of a system process design due to Fig. 3. The sensor data is regarded as the input of the perceptron. In a setup of n_t transponders and n_{AS} antenna sequences specifying the sender-receiver-combination we define $N_{meas} = n_t \times n_{AS}$ measurements for each timeslot resulting in $N_I = N_{meas}$ input neurons.

First tests show, that good results can be achieved with a hidden layer neuron number smaller than the input layer: $N_H \ll N_I$. This assumption also reduces computation time and memory occupancy for our simulations.

The output layer should provide a two-dimensional user position: $N_O = 2$.

The neurons of the second and third layer are calculating their output due to:

$$output = transf(W \times input + B)$$

also shown in Fig. 4., where W is the vector of weightings and B is the vector of bias values. The transfer functions can be defined for the hidden and output layer separately.

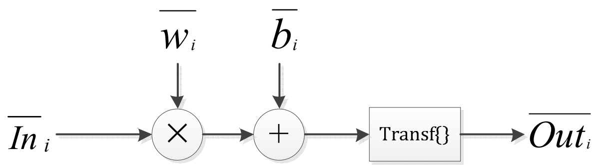

Fig 4: Perceptron activation calculation

Figure 5 is showing a perceptron architecture usable for simple 2-D-positioning. For simplicity reasons we discarded height information und calculate 2-D coordinates. In future a third coordinate could be integrated, because this information is potentially extractable out of the experimental setup.

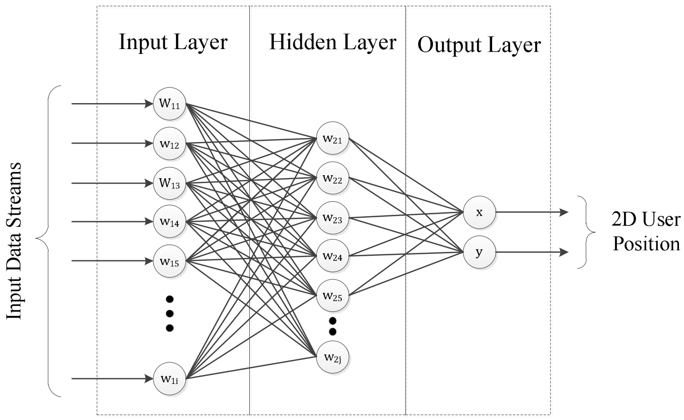

Fig 5: Perceptron structure

IV. SIMULATION

For evaluation we implemented the perceptron with the simulation tool Matlab. The simulation process is described in Fig. 6.

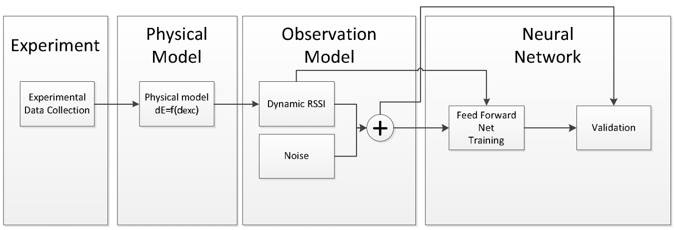

Fig. 6: Data flow of simulation process

After fitting the data from the experimental setup to the physical model, we are able to generate a observation model of observed system behavior. To generate a high number of input data for the network training step we add gaussian-mixture noise to the model data. The noise is calculated from a gaussian distribution with monotonically decreasing variance on the range of d_{exc}, due to the experimental observations. The observation data has two major streams for the neural network. First there is the input stream for the first layer of the perceptron containing the vector of measured signal strength differences dE . Second, there is the target vector P with $\dim(P) = \dim(dE)$ containing the real user position. The observation model can also be used for validation; therefore generated datasets are set as input stream in to the network.
The system parameters of the implemented perceptron model are displayed in Table 2.

Parameters	Value
Input layer neurons	416
Hidden layer neurons	10
Training iterations	1000
Maximum Validation checks	400
Minimum performance	.01
μ_{init}	.1
μ_{inc}	10
μ_{dec}	.01

Table 2: Parameters of NN implementation

The next step is the choice of the transfer function for the different layers. The choice of the transfer function plays a key role for the performance of the system. Typically sigmoid-curves are used for neural network based training approaches, but also linear functions or combination between the different layers are possible. We decided to operate supervised learning and recalculate the weighting matrix by backpropagation. Therefore we evaluated different backpropagation algorithms. First a Levenberg-Marquardt[15] (LM) approach which is often used for training but generally needs much computation time. Hence we decided to try two more algorithms: scaled conjugate gradient[16] (SCG) and resilient backpropagation[15] (RP). With these algorithms the training time of the network could be decreased.

V. RESULTS

In this section we provide the results of the positioning estimation of the perceptron approach. For comparison we defined 13 different user positions within the field, for every user position we used a dataset of 10 measurements. In Fig. 10 the estimates under different system characteristics are pictured. Exemplarily we show the results of the scaled conjugate gradient backpropagation training.
Also shown in table 3 are the *mean squared errors* (MSE) of the neural network outputs. It can be stated that the use of non-linear transfer functions in the hidden layer and linear functions in the output layer leads to best results. Choosing the often used log-sigmoid function in the output layers is leading to the worst results in our experiment. We also evaluated different learning functions for the weighting and bias vector calculation. The choice of the right training function and its truncation conditions has strong influence on the MSE and on the *Time for Training* (TFT). Generally the LM-backpropagation performs best, but with a high amount of calculation time.

Comparing the spread of results we conducted a CDF comparison of the different approaches. In figure 7-9 you can find the comparison for all tested backpropagation algorithms and training function combinations. To facilitate the description we use the following abbreviations: sigmoid (logarithmic-sigmoid), hyp sigmoid (hyperbolic tangent sigmoid).

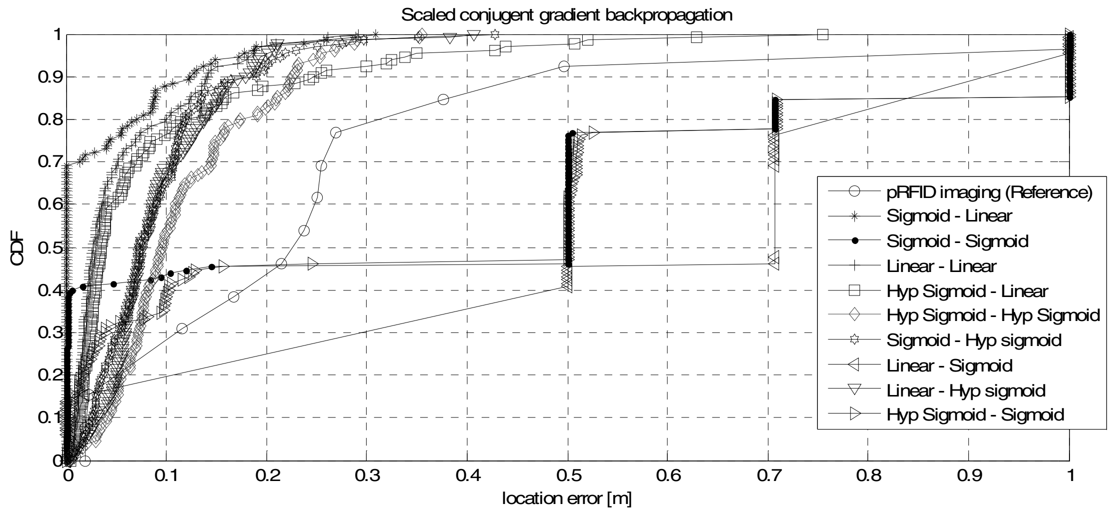

Fig. 7: CDFs of scaled conjugate backpropagation

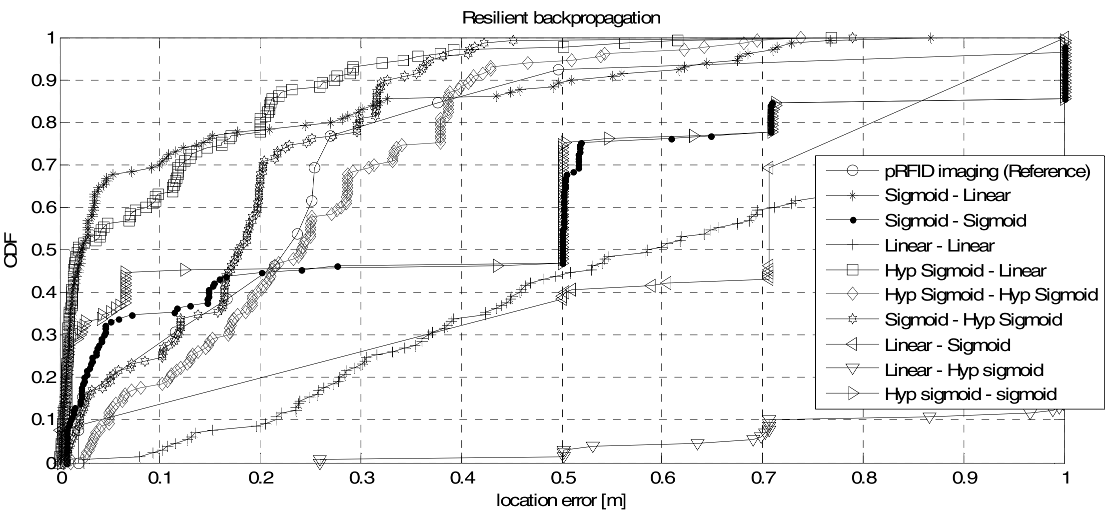

Fig. 8: CDFs of resilient backpropagation

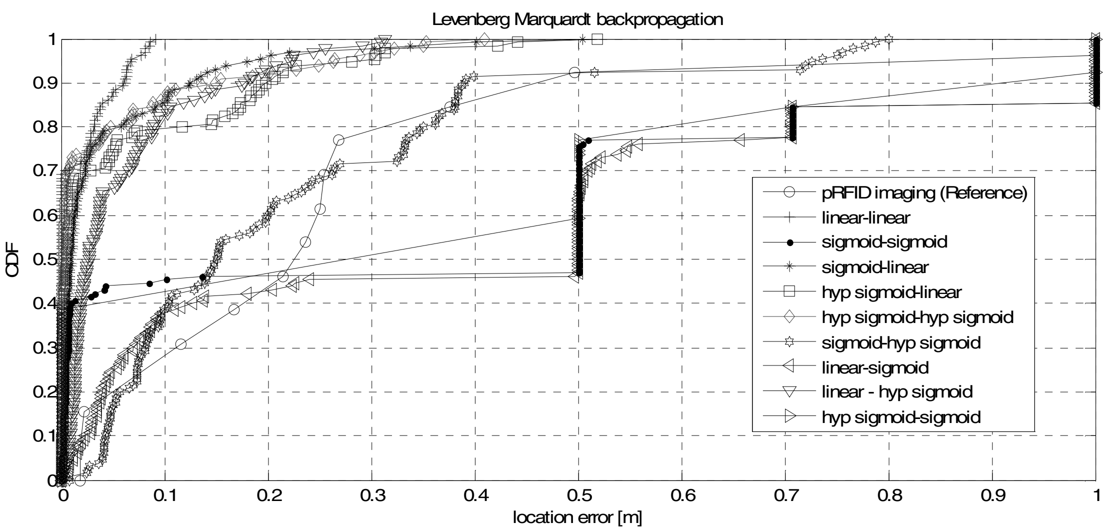

Fig. 9: CDFs of Levenberg-Marquardt backpropagation

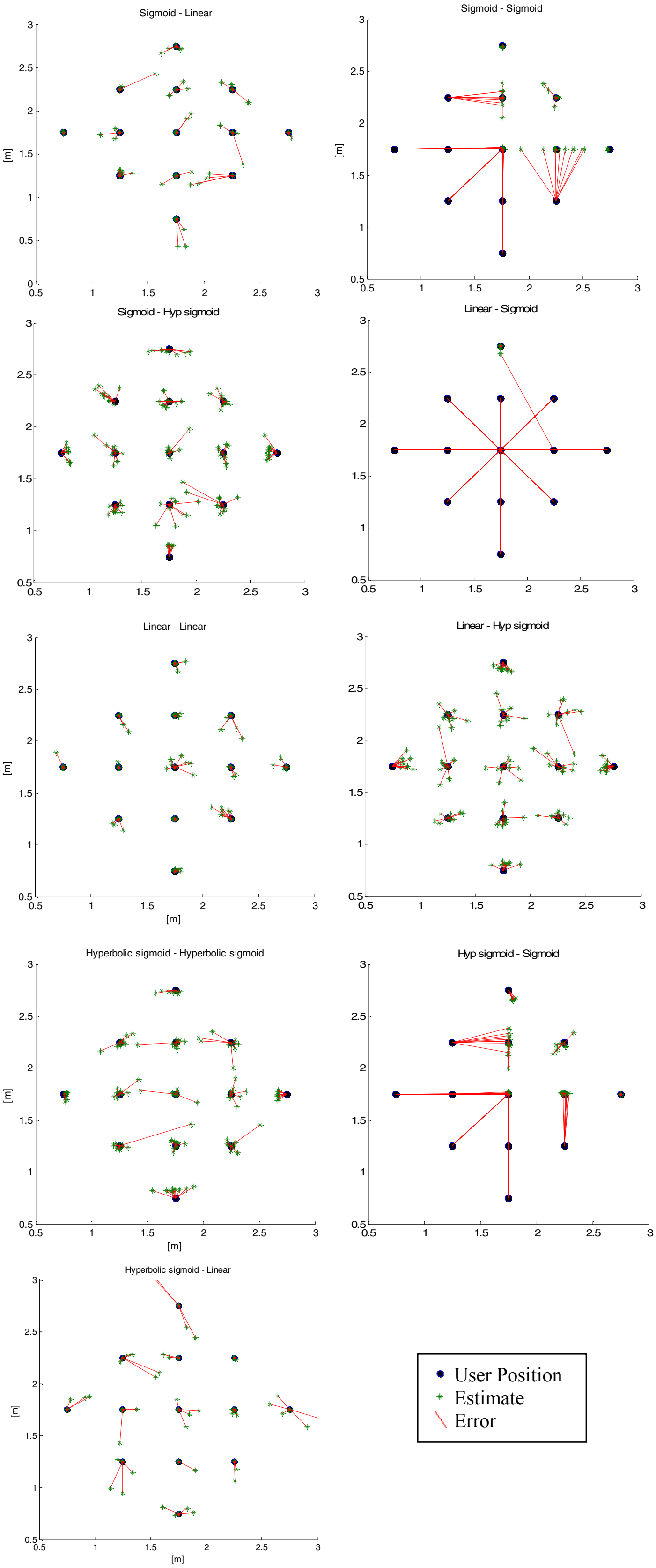

Fig. 10: Positioning results with scaled conjugate gradient backpropagation training

Transf{} Layer 1	Transf{} Layer 2	Train Funct.	MSE [m]	TFT [s][1]
Log-Sigmoid	Linear	LM.	0.0040	212.06
		SCG	0.0026	16.93
		RP	0.0250	6.29
	Log-Sigmoid	LM.	0.1348	4188.58
		SCG	0.1372	9.51
		RP	0.1367	5.88
	Hyperbolic tangent sigmoid	LM	0.0426	4379.36
		SCG	0.0065	7.06
		RP	0.0244	4.43
Linear	Linear	LM.	0.0004	226.00
		SCG	0.0028	18.51
		RP	5.6949	7.99
	Log-Sigmoid	LM	0.1392	419.26
		SCG	0.2341	6.65
		RP	0.2653	5.38
	Hyperbolic tangent sigmoid	LM	0.0042	4298.36
		SCG	0.0065	14.54
		RP	1.1898	0.27
Hyperbolic tangent sigmoid	Linear	LM.	0.0069	210.80
		SCG	0.0110	12.73
		RP	0.0377	7.22
	Log-Sigmoid	LM	0.1442	366.27
		SCG	0.1365	7.29
		RP	0.1376	4.59
	Hyperbolic tangent sigmoid	LM.	0.0045	4171.87
		SCG	0.0074	8.79
		RP	0.0216	8.34

[1]computed on a Intel® Core™ 2 CPU @ 2.66 GHz

Table. 3: System characteristics and results

VI. Conclusion

In this paper we investigated the applicability of multi-layered perceptrons for training-based device-free user localization.

Applying the perceptron approach on the localization problem leads to sufficient estimates for the user positions.

We evaluated the impact of the method of weight matrix calculation and transfer functions; a combination of sigmoid and linear transfer functions was the best choice.

The basis of a high estimation precision is the training of the neural network according to measurements with information about the ground truth. In reality it is difficult to generate a high amount of training data in an experimental scenario. Due to that purpose we will take a look on a certain bootstrapping algorithm based on pre-calculated measurements. Furthermore we will take a look on other classification approaches, i.e. state vector machines (SVM).

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