RSSI-based Localization With Minimal Infrastructure Using Multivariate Statistic Techniques

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***Abstract*—In this paper a new approach to localization of mobile nodes in wireless sensor networks is presented which utilizes the measurement of the received signal strength indicator by multiple receivers concentrated in a small area and applies the technique of linear discriminant analysis to the received data. The concept of gathering all receivers at a single spot provides great flexibility, while good spatial resolution is still achieved. This is demonstrated by a test network operating in the sub-GHz-range around 868 MHz.**

I. Introduction

Localization and location based services (LBS) continue to be a recurring challenge within wireless sensor networks because knowledge about a mobile node's position is necessary to put data received from the node into context and perspective.

Several approaches using position data from the Global Positioning System (GPS), which allow for great positioning accuracy, however only work in outdoor applications and are energy consuming, have been reported like in [1]. Yet – due to energy and cost restrictions – investigations more and more focus on indoor applications and put parameters of the received radio frequency (RF) signal to use.

Phase comparison among linearly aligned and uniquely spaced receivers allow for calculations of the direction of arrival (DOA) [2], but this method requires handling of raw analog RF-data, which usually involves the need for special hardware and phase synchronization. In general, this also comes along with requirements for additional space and energy. Therefore, energy-efficient, low-cost localization approaches using off-the-shelf commercial hardware are typically based on the measurement of the received signal strength (RSS), represented by the received signal strength indicator (RSSI), because this commonly comes as a built-in feature in wireless communication modules.

According to Friis' Transmission Equation in (1) the power measured at a receiver P_r is related to the distance between transmitter and receiver by

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2, \tag{1}$$

for a transmitted power P_t, antenna gains G_t and G_r at transmitter and receiver, respectively, radiation wavelength λ and distance d in an undisturbed environment, in which electromagnetic waves can propagate freely and form a perfectly spherical surface. As pointed out in-depth by [3], there are several sources of RSSI variability and biases. Multipath scattering, fading, and shadowing lead to time-dependent transmission channel properties in case of obstacles within the line of sight between transmitter and receiver or proximity to reflecting items.

Therefore, in this paper a more robust RSSI-based localization algorithm with post-processing of the acquired RSSI-data by linear discriminant analysis (LDA) for a so called fingerprinting is proposed, where a test node's position is calculated in relation to multiple reference nodes.

Similar approaches have been investigated and published by other groups [4], [5]. Yet, they all set up on existing WIFI-infrastructure with fixed access points (APs) distributed over an area of several hundred square meters for RSSI-data-collection, whereas in this approach all the data are collected with multiple receivers located within an area of less than one square meter. This provides great flexibility and allows for setting up a localization network almost anywhere within a short amount of time.

II. Setup

The test-network consists of a battery driven mobile sensor node, which is equipped with temperature, humidity and pressure sensors and controlled by an ultra-low-power integrated transmitter and microcontroller Infineon PMA5110 with wake-up-functionality.

Its signal is captured by three off-the-shelf-receivers consisting of a transceiver Infineon TDA5340 controlled by an Infineon XMC4500 microcontroller mounted on a portable $440\,\mathrm{mm} \times 300\,\mathrm{mm}$-board, as schematically shown in figure 1, and powered by an USB-power-bank.

To ensure that only correct data packages are taken into account for localization, a CRC16-checksum is attached to each package. The acquired RSSI-samples are collected and further processed by MATLAB.

III. Data processing

LDA is a well-established technique used for dimensionality reduction and structure detection in the relationship between

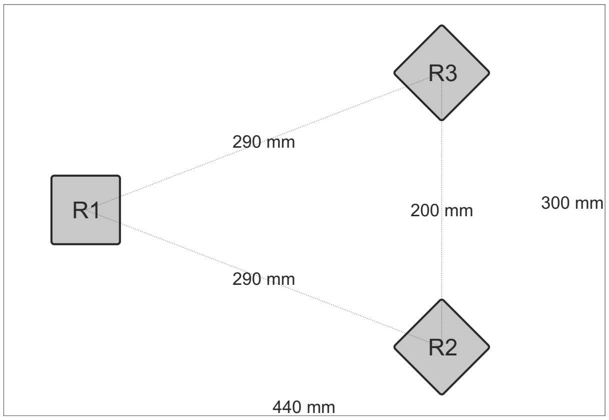

Fig. 1. Scheme of the receiver board

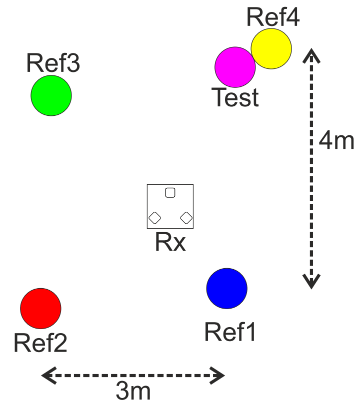

Fig. 2. Setup for spatial resolution test and localization

variables. Therefore, it is employed for maximum likelihood estimations in various areas of application, e.g. the recognition of faces [6].

When a set of variables (RSSI values at different receivers) is measured multiple times with known membership of every sample to a certain group (reference position), LDA solves the problem of maximizing the ratio of between-group-scatter S_B and within-group-scatter S_W [7]. As scatter matrices are proportional to the covariance matrices, the latter can be used for calculations as performed in (2) and (3)

$$\text{Within-group: } S_W = \sum_{c}^{K} \sum_{i}^{N_c} (x_i - \mu_c)(x_i - \mu_c)^{\mathrm{T}} \quad (2)$$

$$\text{Between-groups: } S_B = \sum_{c}^{K} N_c (\mu_c - \overline{x})(\mu_c - \overline{x})^{\mathrm{T}} \quad (3)$$

with N_c representing the number of samples in a group, K the number of groups, μ_c the vector of variable means over the samples in a group, x_i a single sample and $\overline{x}$ the vector of variable means over the whole dataset.

The solution to the maximization problem stated above then turns out to be a generalized eigen-problem

$$S_W^{-1} S_B v = \lambda v \quad (4)$$

for a set of base-vectors v with λ as eigenvalues of the matrix-product $S_W^{-1} S_B$ [7], from which the normalized eigenvectors can be calculated.

To create a new, optimized two-dimensional dataset only the two eigenvectors EV_1 and EV_2, belonging to the largest eigenvalues, are chosen to form a transformation matrix V and the dataset x can be transformed to the new subspace as x^* by

$$x^* = xV \quad (5)$$

After having acquired and processed the reference data, test data can be categorized according to their distance from the group means. For this purpose the squared Euclidean distance D_i of the test sample at coordinates $(P_1|P_2)$ and each group's mean at $(M_{i,1}|M_{i,2})$ is calculated by:

$$D_i = (P_1 - M_{i,1})^2 + (P_1 - M_{i,2})^2 \quad (6)$$

The test sample is then assigned to the group for which D_i is minimal.

IV. Measurements

A. Spatial resolution

To investigate the system's ability to separate between different positions the receiver board was placed in the middle of an office room and four reference positions around it were chosen arbitrarily, as shown in figure 2.

From every reference position 256 samples were acquired, the mean values and standard deviations of the raw data, i.e. before applying the LDA-algorithm, for each position are given in table I.

Measuring and data processing, in total, took 15 minutes. This could further be improved by using a central common control unit for all receivers.

The eigenvalues of the corresponding 3×3-covariance matrix are $\lambda_1 = 41.24$, $\lambda_2 = 4.58$ and $\lambda_3 = 0.07$. This means that 99.86 % of the dataset variance is contained within the direction of the eigenvectors EV_1 and EV_2 belonging to λ_1 and λ_2, respectively.

The data transformed to the new 2D-subspace spanned by EV_1 and EV_2 are shown in figure 3, without any additional filtering and post-processing applied to them. The mean position for each group, which is essential for classifying test data, is displayed in cyan color.

It can be seen that the four reference positions can be clearly distinguished from one another as no overlapping occurs between the four clouds of sample values. The bigger variance of the data in "Ref2" and "Ref3" can be explained

	R1		R2		R3	
Pos.	μ (dBm)	σ (dB)	μ (dBm)	σ (dB)	μ (dBm)	σ (dB)
Ref1	-56.92	0.39	-58.54	0.63	-54.68	0.87
Ref2	-69.94	1.11	-70.60	6.14	-67.74	7.06
Ref3	-84.40	3.00	-75.65	3.36	-74.86	2.67
Ref4	-71.79	0.94	-57.80	0.40	-65.13	0.67

TABLE I
Mean values and standard deviations for the RSS-data of reference positions

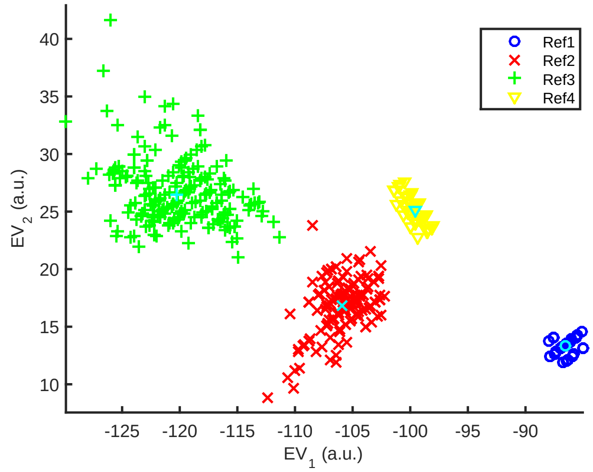

Fig. 3. Reference data transformed to the new 2D-subspace

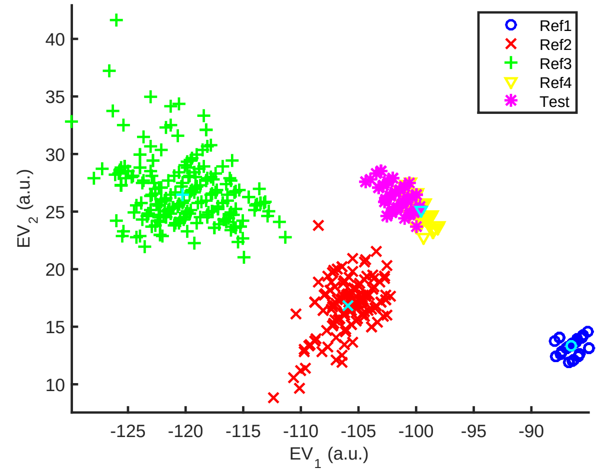

Fig. 4. Localization within the 2D-subspace

	Ref1	Ref2	Ref3	Ref4
Ref1	0	387.4	1306.8	308.8
Ref2	387.4	0	298.1	108.6
Ref3	1306.8	298.1	0	427.1
Ref4	308.8	108.6	427.1	0

TABLE II
SQUARED EUCLIDEAN DISTANCES BETWEEN THE GROUP MEANS

by obstacles appearing in the line-of-sight between receiver board and transmitter during data acquisition. Distances D_{ij} calculated between the mean values are shown in table II.

B. Localization

After proving the system's ability to separate between different positions within the test area the transmitter node was placed at a spot at minimal distance from "Ref4". Another 256 samples were recorded and subsequently transformed to the 2D-subspace according to eq. (5). The results are displayed in figure 4.

When calculating the distance D_i of every test sample to the group means of the four reference positions, the distance to "Ref4" – in account with the real physical setup – is always the shortest.

The mean distances for the test samples are $D_1 = 391.4$, $D_2 = 105.5$, $D_3 = 346.0$, and $D_4 = 5.2$, which allows for an unambiguous assignment to "Ref4" as the nearest neighbor.

Comparing the resulting distribution in the subspace to the actual setup, an axis tilt as well as an inconsistency in the relation between the horizontal and vertical coordinates can be noticed. This hinders localization at positions in between the reference ones because distances in the subspace are not fully proportional to the real dimensions. This issue could be addressed by extended data processing, which uses knowledge about the actual scenario, and refined receiver topology.

V. CONCLUSION

In this work a new approach for RSSI-based localization of mobile sensor nodes with a single base station consisting of multiple receivers concentrated at one point together with measurement results were presented. It has been shown that despite minimum spacing between the receivers good spatial separation of different transmitter positions can be achieved and a nearest-neighbor localization is already feasible without any additional calibration. This offers great potential for quickly set up localization networks. Future refinements of data processing and receiver topology could provide for accurate distance determination.

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