Indoor Location Estimation and Tracking in Wireless Sensor Networks using a Dual Frequency Approach

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***Abstract*—This paper[1] addresses the problem of indoor localization by using wireless sensor networks. The sensor nodes are equipped with two RF front-ends operating at 433MHz and 2.4GHz, respectively. A location estimation and tracking algorithm that exploits the different channel propagation characteristics at the two frequencies is proposed. The ranges are estimated based on received signal strength indicator (RSSI) and path-loss models at both frequencies. The location is calculated by using ordinal multi-dimensional scaling (OMDS). The instantaneous estimates are filtered by using a Kalman filter (KF) together with a simple motion model. The algorithm performance is tested by using real-world measurement data.**

I. Introduction

Indoor localization has been attracting an increasing interest, both in academic and industry research. While the outdoor localization is usually solved by the satellite navigation systems, there is no general reliable solution to the indoor location problem. The main reason is that indoor location is subject to severe propagation conditions and significant non-line-of-sight component in radio frequency (RF) signals. Existing RF-based indoor localization approaches use existing standards (IEEE 802.11 WLAN, IEEE802.15.4/ZigBee, etc.) or dedicated proprietary hardware (e.g. pseudo-satellites).

In this work, we propose a dual-frequency indoor localization algorithm for wireless sensor networks (WSN). This is motivated by the fact that nowadays, cheap sensing devices capable of communicating over multiple wireless interfaces are available (e.g. smart phones incorporate several radio transceivers). The main contribution is that we exploit the different propagation characteristics at two frequencies, 433MHz and 2.4GHz, respectively, for range estimation. The lower frequency signal propagates better inside buildings, through concrete walls, or water (e.g. human body). The higher frequency signal is strongly influenced by the building partitioning as well as by the presence of people due to the high microwave absorption of the water [1]. Exploiting the different propagation characteristics has been considered in the context of radar applications for target localization [2]. The second contribution is an ordinal multi-dimensional scaling (OMDS) algorithm for position estimation that uses a novel distance mapping function. The proposed OMDS algorithm outperforms both the least-squares multilateration [3] and the metric MDS [4]. A Kalman filter approach is employed to reliably track the position over time.

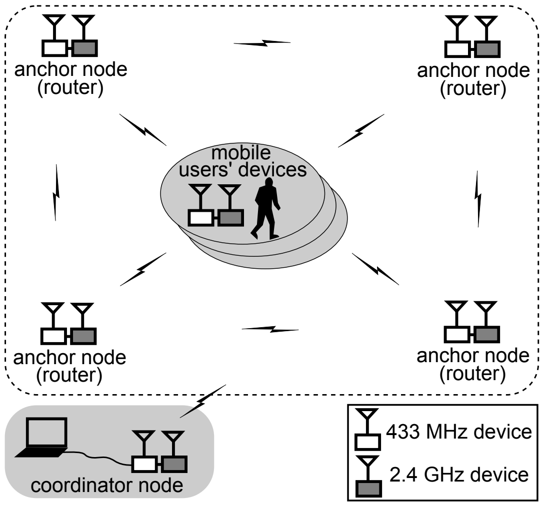

Fig. 1. System model.

II. Network architecture and communication protocol

The network architecture consists of several anchor nodes with known location and multiple user devices, as shown in Fig. 1. They are all equipped with dual frequency transceivers. The centralized localization algorithm runs on an external server, whose gateway is the network coordinator node. The communication protocol is summarized below:

1) The user's device broadcasts a 2.4GHz wake-up message to the neighboring routers

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2) The routers wake up their 433 MHz transceivers from the default energy saving mode
3) Routers reply with a 2.4GHz acknowledge message
4) The end device (mobile user's terminal) broadcasts a 433MHz message to the routers
5) The routers reply with a 433MHz acknowledge message
6) The messages sent by the end device at the two frequencies are used to measure RSSI
7) RSSI information is routed to the gateway for centralized position estimation and tracking

III. Position estimation algorithm

In general, in an indoor environment, the ranges are over-estimated due to severe non-line-of-sight propagation such as shadowing caused by walls and massive objects [5]. Consequently, the position estimates will be highly biased towards a direction opposite to the anchor node. Moreover, the variance of the range estimation error increases with the distance. Therefore, it is desirable to avoid very weak RSSI by selecting fewer, but more reliable neighboring anchor nodes. The proposed dual-frequency ranging approach exploits two basic properties of the wireless propagation channel. The first one is the inherent frequency diversity, i.e., the fact that the two wireless channels may experience different fading statistics. The second property to be exploited is the different capability of the radio waves to penetrate obstacles at the two frequencies. For example, the 433MHz radio waves are considerably less sensitive to the user's body influence and penetrate concrete walls much better than 2.4GHz radio waves [1]. Adding the RSSI information at the higher frequency improves the range estimates in line-of-sight, and provides frequency diversity. Our range estimation is based on two log-distance path loss models that have different path loss exponents n_{LO} and n_{HI} for the higher and the lower frequency, respectively. The estimated distances corresponding to the lower and the higher frequencies are denoted by $\hat{d}_{\mathrm{LO}}$ and $\hat{d}_{\mathrm{HI}}$, respectively. A high difference between these distances indicates that a strong shadowing effect may have occurred, e.g. a wall or some other obstacle. The final range estimate is selected to be the minimum of the two distances

$$\hat{d} = \min\{\hat{d}_{\mathrm{LO}}, \hat{d}_{\mathrm{HI}}\}. \tag{1}$$

This way, the probability of overestimating the range is reduced, especially when severe shadowing occurs.

Multi-dimensional scaling (MDS) [4] is a reliable method to recover the nodes coordinates from multiple pairwise range measurements. Positions can be estimated up to an isometric transformation (rigid motion) that may be removed by using the known position of the anchor (reference) nodes. Metric MDS [4, Chap. 9] minimizes the so-called *stress function* describing the mismatch between the measured distances $\hat{d}$ and the distances corresponding to the current node positions $\mathbf{x} = [x\ y\ z]^{\mathrm{T}}$, for all N nodes, i.e.

$$\mathcal{S}(\mathbf{x}_1, \dots \mathbf{x}_N) = \sum_{m=1}^{N}\sum_{n=1}^{N}\left[\hat{d}_{m,n} - d(\mathbf{x}_m, \mathbf{x}_n)\right]^2. \tag{2}$$

In practice, preserving exact distances is not possible due to the large ranging errors (e.g. incompatible set of distances), especially in RSSI-based ranging. Therefore, the metric assumption becomes unnecessary. Instead of preserving the exact distances between nodes, ordinal MDS [4, Chap. 9] preserves only the ordering of those distances. Thus, the measured distance $\hat{d}$ is replaced by a monotonically increasing function of $\hat{d}$, $f(\hat{d})$, called pseudo-distance (or disparity).

We propose a distance mapping function comprised of two terms, an increasing linear function and a logarithmic function. The function f captures the channel model imperfections and corrects the over-estimated ranges, in average. Its expression is given by

$$f(\hat{d}) = \alpha\hat{d} + \beta\log(\hat{d}+1), \tag{3}$$

with the corresponding coefficients α, β calculated by mapping of the measured distances to the true distances. This function is a monotonically increasing function satisfying $f(0) = 0$. The superiority of the ordinal MDS over the metric MDS has also recently been shown in [6], where time-difference-of-arrival based ranging is used.

IV. Position tracking algorithm

The inherent spatial and temporal correlation between consecutive positions may be exploited in order to filter out the outliers. A Kalman filter approach [7] is used in this paper. The motion components in each dimension are considered to be uncorrelated, and therefore, the tracking can be decomposed accordingly, for each axis[2]. The state vector $\mathbf{s}_i$ at time instant k consists of position p_i and speed s_i along a certain axis $i \in \{x, y, z\}$ (two or three dimensions), i.e., $\mathbf{s}_i(k) = [p_i(k)\ s_i(k)]^{\mathrm{T}}$. The motion model is

$$\mathbf{s}_i(k+1) = \underbrace{\begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}}_{\boldsymbol{\mathcal{F}}}\mathbf{s}_i(k) + \underbrace{\begin{bmatrix} T^2/2 & 0 \\ 0 & 1 \end{bmatrix}}_{\boldsymbol{\mathcal{G}}}\mathbf{w}_i(k) \tag{4}$$

where T is the observation rate, and $\mathbf{w}_i$ is the state noise. The measurement equation is

$$u_i(k) = \underbrace{[1 \quad 0]}_{\boldsymbol{\mathcal{H}}}\mathbf{s}_i(k) + v_i(k), \quad i \in \{x, y, z\}. \tag{5}$$

Both the state noises $\mathbf{w}_i$ and measurement noises $v_i(k)$ are assumed to be uncorrelated, zero-mean, and Gaussian with covariances $\sigma_w^2\mathbf{I}_2$ and σ_v^2, respectively. Under Gaussianity assumption, the Kalman filter is mean-square error optimal. Otherwise, it will be the best linear estimator. The prediction equation (the state estimate) is

$$\hat{\mathbf{s}}_i(k|k-1) = \boldsymbol{\mathcal{F}}\hat{\mathbf{s}}_i(k-1|k-1), \quad i \in \{x, y, z\}. \tag{6}$$

The prediction error covariance matrix is given by

$$\boldsymbol{\mathcal{P}}_i(k|k-1) = \boldsymbol{\mathcal{F}}\boldsymbol{\mathcal{P}}_i(k-1|k-1)\boldsymbol{\mathcal{F}}^{\mathrm{T}} + \sigma_w^2\boldsymbol{\mathcal{G}}\boldsymbol{\mathcal{G}}^{\mathrm{T}}, \tag{7}$$

and the Kalman gain is calculated as

$$\boldsymbol{\mathcal{K}}(k) = \boldsymbol{\mathcal{P}}_i(k|k-1)\boldsymbol{\mathcal{H}}^{\mathrm{T}}\left[\boldsymbol{\mathcal{H}}(k)\boldsymbol{\mathcal{P}}_i(k|k-1)\boldsymbol{\mathcal{H}}^{\mathrm{T}} + \sigma_v^2\right]^{-1}. \tag{8}$$

[2]This is a typical assumption in target tracking (Cartesian coordinates) [8].

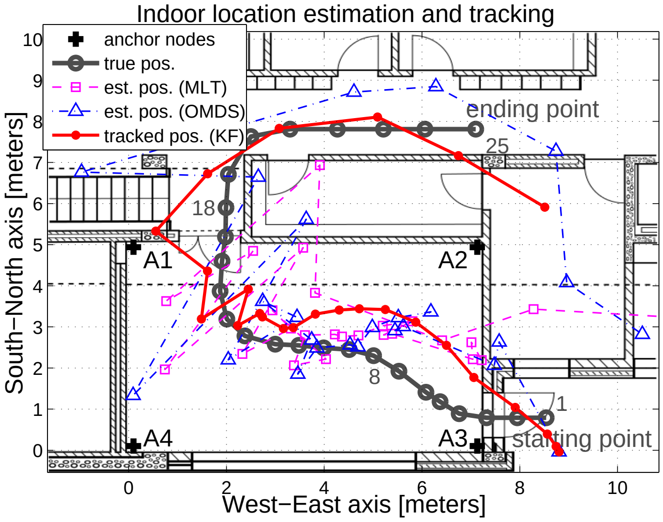

Fig. 2. Comparison between different algorithms: the least-squares multilateration (MLT), ordinal multi-dimensional scaling (OMDS), and the OMDS with the Kalman filter (KF). The position estimates degrade rapidly for the MLT algorithm after leaving the large room where the anchor nodes are located. The OMDS algorithm is capable of roughly estimating the shape of the trajectory. The Kalman filter improves significantly the OMDS estimates.

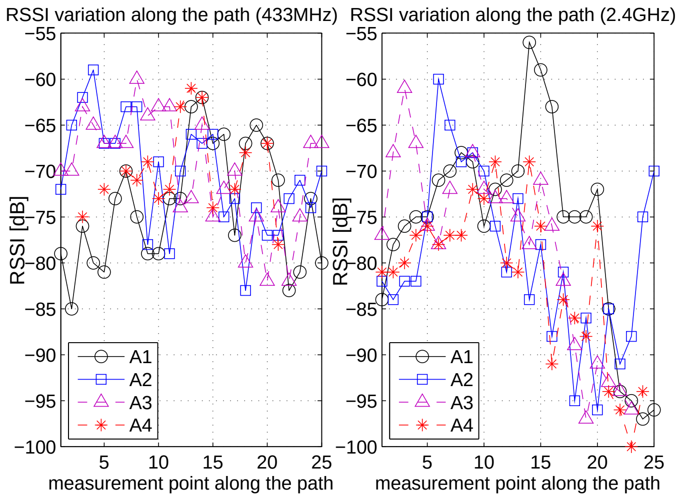

Fig. 3. Mean RSSI variation along the path, w.r.t. different anchor nodes. Strong shadowing phenomena may be noticed after leaving the large room where the anchor nodes are located (see Fig. 2).

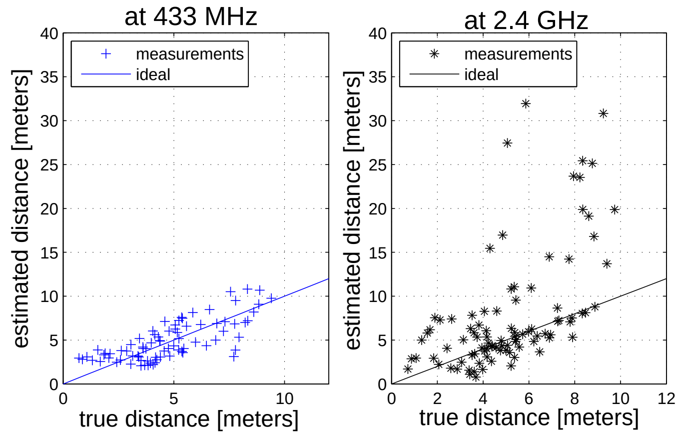

Fig. 4. The true vs. the estimated distances corresponding to the two frequencies (perfect estimation corresponds to the first quadrant bisector). It may be noticed that the estimation is more accurate at the lower frequency. At the higher frequency, the distance is often overestimated.

The estimation error covariance matrix is given by

$$\boldsymbol{\mathcal{P}}_i(k|k) = \boldsymbol{\mathcal{P}}_i(k|k-1) - \boldsymbol{\mathcal{K}}(k)\boldsymbol{\mathcal{H}}\boldsymbol{\mathcal{P}}_i(k|k-1) \tag{9}$$

Finally, the correction equation (the filtered state estimate) is

$$\hat{\mathbf{s}}_i(k|k) = \hat{\mathbf{s}}_i(k|k-1) + \boldsymbol{\mathcal{K}}(k)\big[u(k) - \boldsymbol{\mathcal{H}}\hat{\mathbf{s}}_i(k|k-1)\big], i \in \{x, y, z\}. \tag{10}$$

V. Simulations and Experiments

In our experimental setup, self-made wireless sensor nodes were used, five of them operating at frequency of 433MHz, and other five operating at frequency of 2.4GHz[3]. The motes at lower frequency use an CC1110 chip (Texas Instruments Inc.), and ANT-433-SP chip antenna (Antenna Factor), whereas the motes at higher frequency use a CC2530 chip (Texas Instruments Inc.), and 2450AT43A100 chip antenna (Johanson Technology Inc). The differences between the antenna gains at the two frequencies have been compensated in the software. For measurements and test purposes, motes were programed with a custom application on top of Minimal RF Interface (MRFI) protocol.

We consider the lab environment at IEETA Aveiro, shown in Fig. 2. Four anchor nodes (denoted by A_1, A_2, A_3, A_4 and marked with black crosses) are used to cover the large room and a small part of the corridor. One mobile node[4] whose position needs to be determined moves along the trajectory shown in Fig. 2 by the gray line with circle markers. The mobile user enters the building, crosses the large room, and continues walking along the corridor. The range measurements are taken at the circle markers, with a sampling period of $T = 1$ second. Each measurement is obtained by averaging $M = 10$ RSSI measurements, in order to diminish the space-time selectivity of the fading.

The mean RSSI along the walked path is shown in Fig. 3, with respect to each of the four anchor nodes, at both frequencies. Higher attenuation may be noticed at the higher frequency, especially when a wall obstructs the direct path between user and anchor nodes. The range estimation is based on two different log-distance path loss models whose path loss exponents $n_{\mathrm{LO}} = 2.35$ and $n_{\mathrm{HI}} = 3.1$ correspond to the higher and the lower frequency, respectively, and they were experimentally derived by using our measurements.

Fig. 4 shows the estimated distances plotted against the true distances, corresponding to the two frequencies. A strong impact of the environment is noticed on the RSSI, especially at the higher frequency. The lower frequency penetrates better

[3]The two transceivers will be integrated in the same circuit board.

[4]This is not a limitation of the proposed algorithm, it is only considered for the clarity of the figure.

the walls and obstacles (user's body), The best three anchor nodes in terms of RSSI are used for location estimation and the range is determined as the minimum of the two distances, corresponding to the lower and the higher frequency, respectively. Most of the time, the lower frequency yields a better range estimate, especially in non-line-of-sight, but the higher frequency improves the range estimates in line-of-sight.

The selected range is then input to the proposed OMDS algorithm for position calculation. The distance mapping function is given in (3), with the corresponding coefficients $\alpha = 0.83, \beta = 1.83$ calculated by mapping of the measured distances to the true distances. Although $f(\hat{d})$ is quite close to an identity function, it improves the position estimates by decreasing the mean stress of the network spatial topology graph.

Two different algorithms for position estimation are compared in Fig. 2. The first one is the classical least-squares based multilateration (MLT) technique (see for example [3]) and is shown in Fig. 2 by the magenta dashed line with square markers. The second one is the proposed ordinal multi-dimensional scaling (OMDS) and is shown in Fig. 2 by the blue dot-dashed line with triangular markers. It may be seen that the OMDS algorithm outperforms the classical MLT algorithm whose estimates deviate further away from the true path. In our experiments, we found out that even the metric MDS outperforms MLT. The influence of the human body on the position estimates may also be noticed Fig. 2 after the user enters the large room. The user holds the sensor node in his right hand with antenna aligned to the direction of motion. When his body starts to obstruct the line-of-sight to the anchors nodes A_3 and A_4, the estimated position tends to be deviated away from these anchor nodes (see Fig. 2). We found that without using the lower frequency, the range is severely overestimated, thus making the position estimation very challenging.

The OMDS estimates are incorporated into the Kalman filter (KF) in order to perform the position tracking and eliminate the unreliable position estimates. Initial state vector consists of the initial position estimated by using OMDS and zero initial speed. The measurement noise standard deviation is set to $\sigma_v = 12.2$, based on our measurement data. The state noise standard deviation is set to $\sigma_w = 1$. This value is intuitive in the sense that we can trust the motion model more than the measurements. The predicted path (red continuous line with dot markers in Fig. 2) is close the true path, considering that no information about the geometry of the building was used. For this environment, the mean position estimation error are $\bar{e}_{\text{MLT}} = 2.20$m, $\bar{e}_{\text{OMDS}} = 1.98$m and $\bar{e}_{\text{OMDS+KF}} = 1.30$m, for the MLT, the OMDS alone, and the OMDS with the Kalman filter, respectively. The standard deviations of the position estimates are $\sigma_{\text{MLT}} = 1.65$m, $\sigma_{\text{OMDS}} = 1.51$m and $\sigma_{\text{OMDS+KF}} = 0.68$m, respectively (see Fig. 5).

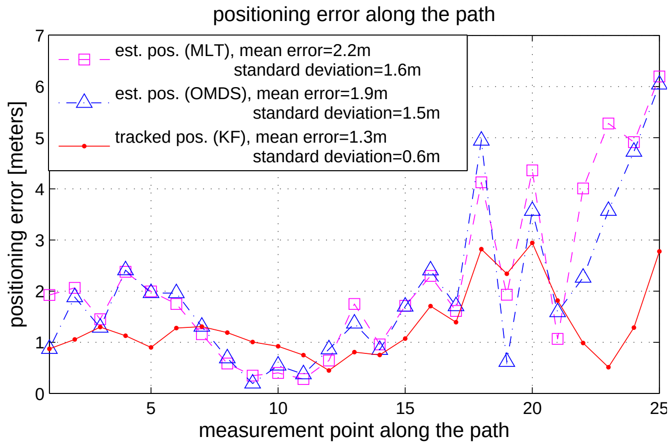

Fig. 5. The position estimation error of the least-squares multilateration (MLT), ordinal multi-dimensional scaling (OMDS) and OMDS algorithm with the Kalman filter (KF). Although the difference between the MLT and the OMDS position estimation algorithms does not appear to be very large, the corresponding trajectories are quite different (see Fig. 2). .

VI. Future Work

In terms of future work, exploiting the RSSI information gathered at two different frequencies will be further investigated. The extension of the proposed scheme to cooperative positioning will also be considered. More advanced motion models will be employed, together with computationally attractive Bayesian filters for position estimation and tracking that do not require Gaussianity for optimality.

VII. Conclusions

A dual-frequency position estimation and tracking algorithm for indoor environments was proposed. The position estimation relies on an ordinal MDS method, and the tracking is done by using a Kalman filter with a simple motion model. The algorithm performance is simulated in an lab environment by using parameters derived from measurements. The estimated path of the mobile node is close to the true path, considering that no knowledge about the building geometry was assumed.

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