Anomaly-based Device-free Localization with Particle Filtering

Marco Cimdins*, Mathias Pelka* and Horst Hellbrück*
* Luebeck University of Applied Sciences, Germany
Department of Electrical Engineering and Computer Science
Email: marco.cimdins, mathias.pelka, hellbrueck@fh-luebeck.de

***Abstract*—In the Internet of Things (IoT), devices, e.g. sensors or actuators, transmit packets to transfer data. For the IoT localization information is crucial, as it provides additional context for the data. We envision that devices in the IoT know their position and on receipt of a packet, the received signal strength is measured. This measurement is used to build a device-free localization (DFL) system to improve the dependability of the IoT system. DFL systems are able to detect and track persons within a target area that neither wear a device nor participate actively in the process of localization. This work presents an anomaly-based DFL system that measures if a person affects the radio frequency (RF) propagation and determines the position with a particle filter. In our 65 m^2 indoor testbed, we employ eight IEEE 802.15.4 compliant wireless transceivers and estimate the position of a person with a median localization error of 1.4 m.**

***Index Terms*—device-free localization, device-free localization applications for the IoT, robust localization.**

I. Introduction and Related Work

Localization is considered key for the *Internet of Things (IoT)* where devices, named *Things* are equipped with sensors and communication interfaces. In the past, dedicated hardware for localization was employed, e.g. localization based on phase measurements [1] or UWB [2]. Despite quite successful, dedicated hardware increases cost and complexity of devices.

Additionally, new applications emerge, for instance, tracking of goods or surveillance of assets. However, in some instances, e.g. plant security, an intruder does not carry a device to track. For such scenarios, *device-free localization (DFL)* systems are suitable and expand IoT systems: First, DFL systems complement active localization measurements by triggering an alarm when the position of the active and device-free localization system does not match or second, the DFL system detects a person that does not carry a device. DFL systems exploit the change of radio propagation to detect and track persons within a target area. This is done by measuring the received signal strength (RSS) e.g. as shown in [3], [4] or via special sensor radars that measure the time-of-arrival [5]. As shown in Figure 1, the radio propagation is distorted, when a person or another obstacle is present. This allows tracking, even when persons do not carry any devices. This tracking of distortions even for standard communication devices is helpful to increase the robustness of IoT systems when systems forecast link qualities and avoid weak links beforehand.

RASID [6] was one of the first anomaly-based DFL systems and records a *silence profile*, which serves as a basis to detect an *anomaly* in the radio frequency (RF) propagation. In a second step, anomaly detection was extended with a particle filter, to allow tracking of persons [7]. Compared with other DFL systems, e.g. fingerprint-based localization systems, anomaly-based localization systems are easily calibrated during a calibration phase, whereas fingerprint-based systems require an extensive collection of fingerprints [3], [6]. In the past, IEEE 802.11 RSS measurements have been investigated for DFL. IEEE 802.15.4 allows implementation of cost-effective radio interfaces with low power consumption that are suited for the IoT.

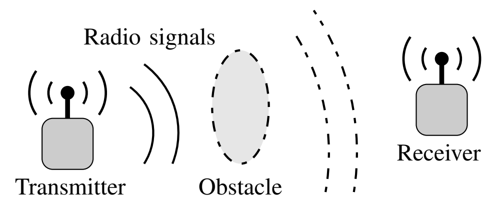

Fig. 1: Radio propagation obstructed by an obstacle.

In contrast to our previous work in [8] where we detect presence of persons only, we add tracking functionality via particle filtering in this publication. Different to [6], [7], our DFL system runs with IEEE 802.15.4 compliant transceivers.

The contributions and structure of this paper are as follows: In Section II, we present a DFL system based on anomaly detection using IEEE 802.15.4 RSS measurements. Next, we present our approach with a particle filter, mobility model and elliptical weighting function calculated from the anomaly values. In Section III we present implementation details. Section IV discusses the results. Finally, we provide a summary and an outlook to future work in Section V.

II. Description of the DFL System

In this section, we introduce anomaly detection that determine the presence of a person and a particle filter that estimates the position.

A. Anomaly-detection

Anomaly detection was first introduced by Kosba et al. in [6]. The main idea is to record a probability density function (PDF) of each stream, while the target area is vacant in a calibration phase and analyze it for anomalous behavior during an online phase. We implement the same steps as in [6] and [8] according to Figure 2.

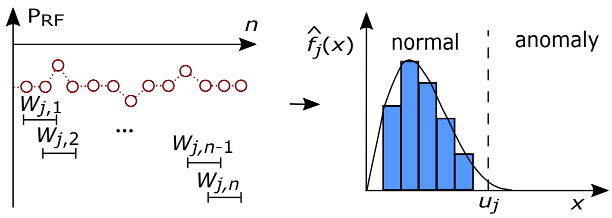

Fig. 2: Principle of anomaly detection.

In a calibration phase, when a target area is vacant, RSS values for k streams are recorded (Figure 2). A *stream* is the continuous transmission of packets that results in RSS measurements. For each stream j, a feature value $x_{j,n}$ with time step n, is calculated from a sliding time window $W_{j,n} = [s_{j,n-l+1}, s_{j,n-l+2}, ..., s_{j,n}]$ with the length l, where $s_{j,n}$ is the RSS value. In our solution, we select the variance as a feature value as suggested by [6], [7]. We aim to track moving persons that result in high variances due to changes of the RSS. The PDF $\hat{f}$ of each stream j is estimated with a kernel density estimator. With $\hat{F}_j$ is the cumulative distribution function (CDF) of $\hat{f}_j$, we calculate the upper bound $u_j = \hat{F}_j^{-1}(1-\alpha)$. α is the significance parameter, for dispersion features, such as the variance, we calculate the $100(1-\alpha)^{th}$ percentile of the CDF $\hat{F}_j$. The estimated PDF $\hat{f}_j$ and the upper bound u_j are the silence profile for each stream j.

During the online phase, RSS are recorded for k streams, the feature values $x_{j,n}$ are calculated from the sliding time windows with length l $W_{j,n} = [s_{j,n-l+1}, s_{j,n-l+2}, ..., s_{j,n}]$. A stream is considered anomalous when $x_{j,n} > u_j$, this is described in terms of the anomaly score $a_{j,n}$:

$$a_{j,n} = \frac{x_{j,n}}{u_j}, \text{where} \begin{cases} a_{j,n} < 1 & \text{if no anomaly is detected} \\ a_{j,n} \geq 1, & \text{if anomaly is detected} \end{cases} \tag{1}$$

In order to detect a person moving within a target area, the anomaly scores $a_{j,n}$ for all streams are summed up to a global anomaly score a_n and are smoothed exponentially. For details on RSS samples, variances and anomalies, we refer to [8]. In the IoT, anomaly detection is one option to detect weak links, which is a first step to increase the robustness of the system.

B. Particle Filter

This section describes a particle filter that estimates the position of a person within a target area based on anomaly scores. Particle filters are sequential Monte Carlo methods that estimate probability densities through random samples, called particles, where N_s are the number of particles. Specifically, for our DFL system, we use a variation of sequential importance sampling with resampling (SIR) filter, named bootstrap filter. Given the RSS vectors $\mathbf{s}_n$, we will estimate a position $\mathbf{r}_n$ of a person. The algorithm works as follows [9]:

1) Draw a new position $\mathbf{r}_n^i$ for every particle within the particle set $\mathbf{r}_{n-1}^i : i = 1, ..., N_s$:

$$\mathbf{r}_n^i \sim p(\mathbf{r}_n|\mathbf{r}_{n-1}^i), \quad i = 1, ..., N_s. \tag{2}$$

2) Calculate the particle weights:

$$w_n^i \propto p(\mathbf{s}_n|\mathbf{r}_n^i), \quad i = 1, ..., N_s. \tag{3}$$

Normalize over the sum of the weights.

3) Resample N_s particles from the particle set.

Note, to avoid convergence problems resampling is performed for every time step n. For RSS vectors $\mathbf{s}_n$ we use anomaly scores $a_{j,n}$ as described in the previous section. Therefore, we determine the mobility model $p(\mathbf{r}_n|\mathbf{r}_{n-1})$ in Section II-B1 and the importance function from (3) in Section II-B2. We describe the particle with the following states.

$$\mathbf{r}_n^i = [x_n^i \ y_n^i \ v_n^i \ \theta_n^i]^T, \tag{4}$$

where x_n^i, y_n^i is the 2D-position, v_n^i the velocity and θ_n^i is the heading of the ith particle.

1) Mobility Model of a Person: The goal of the mobility model is to create a particle set that is able to follow a movement of a person. The mobility model estimates the new position of a particle dependent given the last state.

$$\mathbf{r}_n^i = \begin{bmatrix} x_n^i \\ y_n^i \end{bmatrix} = \begin{bmatrix} x_{n-1}^i + v_n^i \cos(\theta_n^i)\Delta n \\ y_{n-1}^i + v_n^i \sin(\theta_n^i)\Delta n \end{bmatrix}. \tag{5}$$

where $v_n^i = v_{n-1}^i + v_{n,\text{noise}}^i$ and $\theta_n^i = \theta_{n-1}^i + \theta_{n,\text{noise}}^i$. The starting particle set is given as $\theta \sim \mathcal{U}(0, 2\pi)$ and $v \sim \mathcal{N}(1.0\,\text{m/s}, 0.3\,\text{m}^2/\text{s}^2)$. In every time step Δn noise is added to the particles to account for uncertainties:
$\theta_{\text{noise}} \sim \mathcal{N}(0, \sigma^2_{\theta\text{noise}})$ and $v_{\text{noise}} \sim \mathcal{N}(0\,\text{m/s}, \sigma^2_{v\text{noise}})$.

2) Importance function: The importance function calculates a weight of each particle i depending on measurements and the actual position of a particle. For every stream j the particle weight is calculated as follows:

$$w_{j,n}^i = a_{j,n} \frac{d_j}{d_{S1,j}^i + d_{S2,j}^i} \tag{6}$$

Figure 3 shows the relation between the transceiver positions and the ith particle from (6).

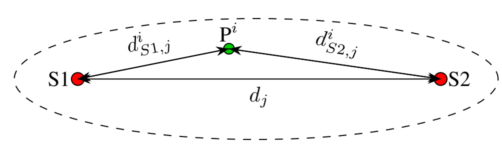

Fig. 3: Importance function.

The weight of particle i is maximized, when the particle is located within the line-of-sight (LOS) of the stream. This is due to empirical studies, where the change in RSS is typically the greatest when a person is within the LOS of the stream [7]. The further away from the LOS, the lower the weight of the particle. During resampling, N_s new particles are sampled based on their weight, the lower the weight the less probable it is for the particle to be resampled. The effect is that only those particles survive that are close to a position of a person. In future, a more adaptive importance function will take the state of the stream and the result of the position estimation into consideration. After weights for all N_s particles and k streams have been calculated, the weight of particle i is the mean of the weight of k streams. With tracking of persons, it is possible to predict future link failures and therefore increase the robustness of the IoT system.

III. Implementation

To evaluate the proposed DFL system, we setup a 65 m^2 indoor testbed with eight transceivers that are mounted on existing brackets at a height of 2.4 m. In general, when the transceivers are mounted in the same height as the person, we expect higher RSS variances.

Transceivers controlled by an Atmel ATxmega128A1 are equipped with an Atmel AT86RF233 radio chip compliant to IEEE 802.15.4. In previous work, we compared received signal strength indicator (RSSI), energy detection (ED) and link quality indicator (LQI) value for DFL measurements [8]. We find that the ED serves best, as it offers the highest resolution of 1 dB in a range of –94 dBm to –10 dBm. For eight transceivers, we use a sampling rate of 80 ms. The current state of our system processes only single hop streams between transceivers. Other streams are recorded and also available for future processing. Figure 4 shows our testbed. The red circles are the positions of the sensor nodes, the dashed lines indicate the streams.

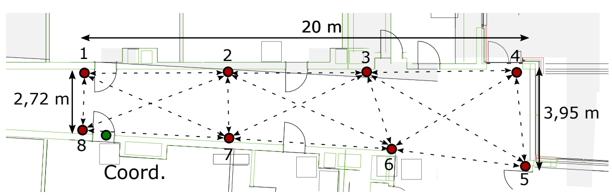

Fig. 4: Measurements of the testbed. The red circles are the sensor nodes, the dashed line the streams.

IV. Evaluation

This section evaluates the tracking performance of the proposed DFL system. We envision that DFL systems are integrated into IoT systems and that detection and tracking of persons result in predicting of links that will be interfered through man-made impairments. The localization error for every time step n is the Euclidean distance between the ground truth position and the position estimation. Throughout the tests, following parameters were chosen: For the kernel density estimator, we select an Epachnikov kernel, a window size $l = 15$, a significance parameter $\alpha = 6$, and a particle set with $N_s = 500$. We tested six different walking patterns within the target area and repeated the measurements up to four times. The walking patterns comprise several routes through the target area, e.g. entering from the left and leaving to the right, entering and wait in front of a bookshelf, etc. In order to receive statistical sound results for the localization error, 100 realizations of the DFL system were performed for each measurement. We determined the median localization error as 1.4 m and the 95 percentile is 4 m. Figure 6 shows an exemplary realization. The person started top right and walked with a velocity of 0.5 m/s in clockwise direction.

Figure 5 shows the particles (gray circles), the position estimation (black cross) and the ground truth of the person (blue circle) at two different times. Figure 6 shows that the position estimation relates to the movement of the person. However, in our indoor testbed especially in the very right part, we experience high anomaly scores although the person is several meters away from the streams. We assume that this is caused by multipath effects that change the RSS significantly and therefore, degrade the localization performance.

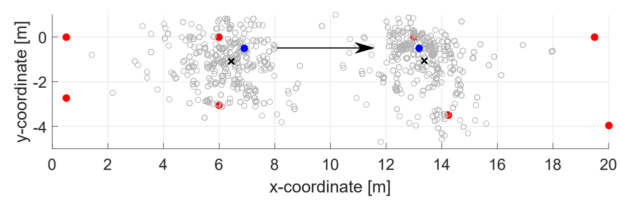

Fig. 5: The blue circle is the ground truth, the black cross the position estimation. The gray circles are the particles.

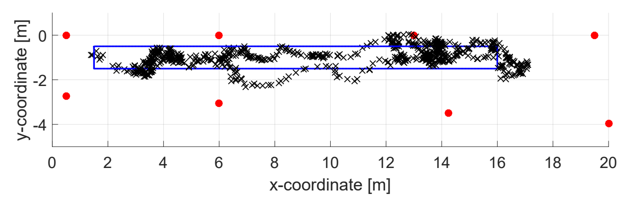

Fig. 6: Exemplary result. The red circles are the sensor positions. The blue line indicates the ground truth (walking with 0.5 m/s, starting point is top right in clockwise direction). The black crosses are the position estimations.

V. Conclusion and Future Work

In this work, we detect whether a stream is affected by a person with anomaly detection and present a SIR particle filter to estimate the position of the person. The median localization error is 1.4 m and the 95 percentile is 4.0 m. In future, we will investigate how much our DFL can improve the dependability of networks and active localization systems for the IoT by predicting moving persons. Additionally, we will improve the accuracy of the system by investigating methods to process data according to a RF propagation model and adapt the importance function accordingly.

Acknowledgments

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