An indoor localization system based on particle filters and real-time range-free estimation method

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In this work, we present an indoor localization system based on Wi-Fi technology and a range-free based method. The localization method makes use of the main results obtained reported in our ongoing research efforts [2]. The mobile device, in our case a smartphone, captures the Received Signal Strength Indicator (RSSI) of the APs to triangulate the user's position.

Range-free based methods exploit the relationship between RSSI and distance. In general, the closer the distances to AP, the higher the RSSI value (around -30 dB). However, this relationship does not always hold, since the indoor environment and the radio propagation channels characteristics can cause unexpected RSSI fluctuations. These fluctuations translate into noise. Our approach focuses on reducing the impact of the noise over the position and tracking estimation of the target mobile device. Furthermore, it is able to identify unfeasible displacements misleading the localization, such as a huge change on the postion of the target within a short period of time. In our case, our approach estimates the current position taking into account previous estimations.

To reduce noise from RSSI, we implement a particle filter based indoor localization algorithm. This technique uses the Bayesian theory to process sequentially signals that contain noise with the aim of estimating a time-based system state. Instead of having a single hypothesis, a particle filter uses many hypotheses (particles), each with a corresponding importance weight. The set of particles and the corresponding weights represent a probability distribution over the space of possible localizations.

We use the range-free based model proposed in [4], and expressed by the following equation:

$$P_r(d) = P_r(d_0) - 10 \cdot n \cdot \log\left(\frac{d}{d_0}\right) \qquad (1)$$

where $P_r(d)$ is the received strength, $P_r(d_0)$ is the received strength at d_0 meters, n is the path loss coefficient factor and d is the distance between AP and user. The path-loss coefficient factor expresses the Wi-Fi signal spread within a given environment.

Some research works [1, 3] conclude that the path-loss coefficient factor value in indoor environments has to be in the range from 2 to 4. Most indoor localization systems performs a calibration process consisting on the sampling of the RSSI in several known positions and computing a single value of n for each AP. However, we have shown that this approach has severe limitations [2], since the signal propagation channel changes over time. The value of n must then be adjusted in real-time given the information of the propagation channel.

From Eq. (1) we can see that RSSI ($P_r(d)$) and path loss coefficient factor (n) are inversely proportional. Figure 1, which plots RSSI and path loss coefficient factor over time, shows such relationship. An increase on RSSI results on a lower n. Therefore, if we know the real value of n_i, we can estimate the value of n_{i+1} based on RSSI variation. However, this approach is only appropriate when the user is stopped, since varying n according to RSSI variation doesn't produce a change in distance estimation.

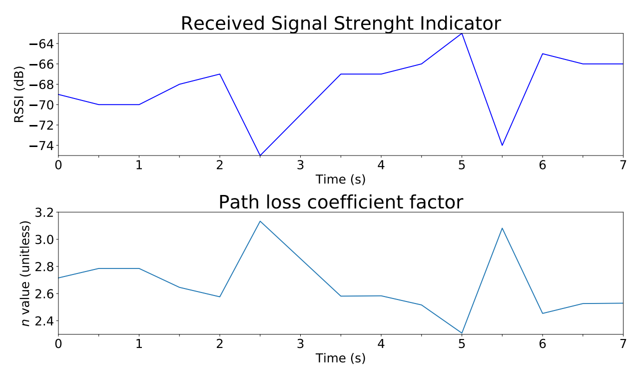

Figure 1: RSSI and real n value over time

In order to avoid this, we perform an RSSI capture following a predefined path in our experimental environment. From this data, since we know the true distance to APs, we can compute the exact value of n. Figure 2 plots the correlation between n and distance to one of the AP. Closest distances to AP (less than 1 meter), correspond to large values of n. This is due to the fact that in those positions the RSSI barely varies, consequently the proximity to an AP causes a large increase of n. In distances between 1 and $4m$, the n value decreases to less than 2. Thereafter, the n value begins to increase until reaching a value close to 3. However, there is not always an increase, which is due to the environment characteristics and, most especifically, to the signal occlusion caused by humans.

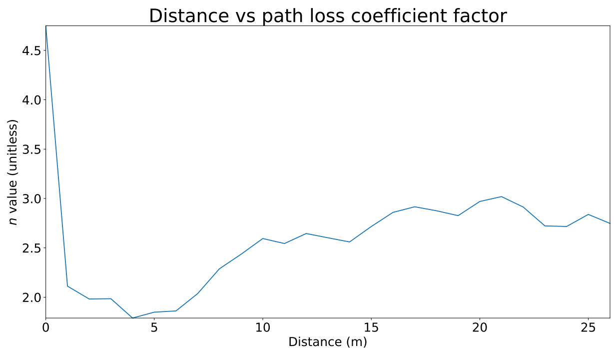

Figure 2: Distance vs real n value over time

In summary, the proposed estimation of n can be expressed by:

$$n_i = n_{i-1} - (P_{r,i} - P_{r,i-1}) \cdot \alpha + \Delta d \cdot \beta \quad (2)$$

where $P_{r,i}$ is the current received strength, $P_{r,i-1}$ is the previous received strength, α is a factor that express the relationship between RSSI variation and n variation, Δd is the distance variation and β is a factor that express the relationship between distance variation and n variation. Both α and β are factors that depend on the smartphone and the environment.

Eq. (2) introduces a new unknown: Δd. That is, we need to know the distance between the current position of the target with respect to the previous sample and, most specifically, if the user get closer or moved away from the AP. Since this system is designed for smartphones, we can use embedded sensors of this devices to build a Pedestrian Dead Reckoning System (PDRS) [5] to estimate this information. Actually, our approach makes use of such facilities.

Figure 3 depicts the architecture of our indoor localization system. The smartphone captures RSSI from Wi-Fi platform APs and its embedded sensor readings. This information is passed to the localization server, which, first, estimates a path loss coefficient factor value (equation 2) and, later, obtains the distance prediction using Eq. (1). The particle filter is subsequently fed with the predicted distances in order to weight all the particles and finally predicts the user's position.

A critical point of our system is to obtain the real first path loss coefficient factor value. If we fail estimating this value, the system will accumulate error and, surely, will not work properly. In order to avoid this, our approach includes the:

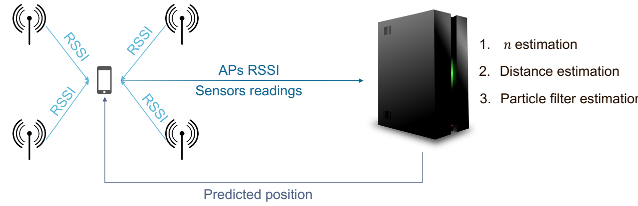

Figure 3: Overall proposal scheme

- Feeding the system with the first true position.
- Use of the m first RSSI captures to properly estimate the value.

The calibration procedure of our localization system is as follows:

1. Deploy several APs in known positions of the environment (at least one in each corner). Therefore, we need to know the environment dimensions in order to calculate APs' coordinates.
2. Walk through a predefined path. This process provides us the following information (used to train the models making up the entire system):
   - User's movement habits.
   - Relationship between RSSI and n.
   - Relationship between distance and n.

Once calibrated, the indoor localization system is able to locate the user in real-time. Anyway, the system can continue feedback itself with the real-time localization. For example, it could detect areas where users cannot be placed, such as tables or furniture.

1. REFERENCES

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