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Ultra-Wideband Localization in for Person Tracking

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Abstract

The UWB tracking system has gained, over these last few years, a big attention. More studies started to explore this domain. The UWB system provides us a localization indoor with a big precision. In this paper, we are going to focus on the effect of a crowd of people on the localization, and we are going to study some filters and their efficiency.

Filters

We considered multiple filters for our scenario, we went from the most basic one which is the Kalman filter, to a special implementation of the particle filter, called the Kalman-Like Particle Filter.

We also implemented a particle filter that relies on the Kalman filter estimation of the velocity. This velocity is considered as the dynamic model for our particle update step. After that, we calculate the weight of each particle based on both values: the measurement and the Kalman filter estimation of the position.

$$w_t^k = \exp - \left(\frac{(x_t^k - \tilde{x}_t)^2}{2(\sigma_{n_x})^2} + \frac{(y_t^k - \tilde{y}_t)^2}{2(\sigma_{n_y})^2} \right) + \exp - \left(\frac{(x_t^k - x_t^{kal})^2}{2(\sigma_{n_x})^2} + \frac{(y_t^k - y_t^{kal})^2}{2(\sigma_{n_y})^2} \right)$$

In the next section, we are only going to focus on the Kalman-like Particle filter, we will provide a brief explanation, concluding with the algorithm of this filter.

Kalman-Like Particle Filter

The KLPF is a new implementation of the particle filter, it starts by generating a set of particles, it then applies a Kalman filter on each of those particles to transit them. In this case, the update step is the Kalman filter. It then weights the particles and resamples them.

One of the main advantages of the Kalman-like Particle filter over the other filters is the low computational cost. It needs far fewer particles than the others.

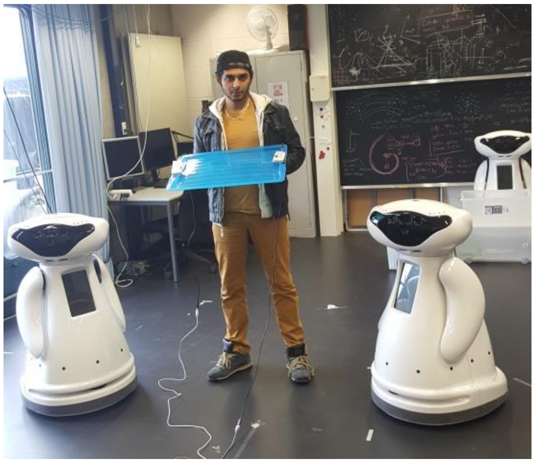

Figure 1: Tracking setup

Influence of the human crowd on the localization

We've run multiple of experiments to define the effect of the human body on the signal. We noticed that, indeed, when the tag's holder is in between several people, the signal starts overshooting, it goes from 0.28m to 0.41m. Adding a second tag helped us reduce this error, we manage to get a final error of 0.27m. But the most interesting part was that the tag's holder's own body, even when no one was around, was a major factor to the addition of the error on the measurements, it increases from 0.14m to 0.29m.

Conclusion

The Kalman-Like Particle filter was able to reduce the total error in our experiments going from 0.35m to 0.21m, but it wasn't able to suppress the Non-Line of Sight measurements. With the addition of a second tag, we had the possibility to differentiate between the LOS and the NLOS measurements, which decreased a lot the overshoots on our data. Making the tracking more viable and precise.