A Real-Time Indoor Localization Method with Low-Cost Microwave Doppler Radar Sensors and Particle Filter

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Abstract. We propose a novel method of localization based on low-cost continuous-wave unmodulated doppler microwave radar sensors. We use both velocity measures and distance estimations with RSS from radar sensors. We also implement a particle filter for real time localization. Experiments show that, with a reasonable initial estimate, it is possible to track the movements of a person in a room with enough accuracy for considering using this type of devices for monitoring a person or indoor guiding applications.

Keywords: Indoor localization · Doppler radar · Particle filter · Electronic travel aid

Indoor monitoring elderly people or guiding visually impaired persons (see e.g. [1]) need accurate and fast real-time localization systems. Indoor positioning is a very active research topic, and many technologies have been developed in this field (see e.g. the survey [2]). Nevertheless, unmodulated continuous wave doppler radar has been little explored for pure positioning applications, although they could be inexpensive and simple to deploy. Doppler radars are widely used in presence detectors (door opening) as well as for vehicle speed control. Unlike frequency-modulated continuous-wave (FMCW) or pulse radar, they do not measure distances. Instead, they may determine the radial velocity components of moving objects in the field of the radar.

We propose in this paper to use meager cost and rudimentary radar modules (see Fig. 1) originally designed for presence detection. This opens the door to very low cost monitoring or blind guidance applications. Unlike metrology grade sensors (e.g. Doppler radar for road control), miniature microwave radars offer minimal accuracy in the counterpart of their low cost (about 10 euros).

Those devices are used in research projects for many applications. Some researchers use them for gait monitoring and movement classification [3, 4], while others try to estimate the walking speed [5] or investigate guidance and obstacle avoidance applications [6]. At first sight, it seems unreasonable to use these sensors alone to locate a person because they do not provide absolute distance measurements. This is why some researchers have used Kalman filters to combine
these radar measurements with more reliable technologies that measure distances (e.g. UWB, see [7]).

We here propose a different approach in which we use the Received Signal Strength (RSS) of the radar in order to obtain a distance evaluation.

1 Measurements Model

According to the Doppler effect equation, the speed $v$ measured by the radar can be written as:

$$v = \frac{c f_d}{2 f_{tx} \cos(\alpha)}$$

(1)

with $c$ the speed of light, $f_d$ the Doppler frequency, $f_{tx}$ the frequency of the radar signal (typically 24 GHz) and $\alpha$ the angle formed between the direction of motion and the radar beam. Notice that, for our practical application, the Doppler signal contains several frequency components related to the limb movements of the subject.

As already explained, these sensors are not designed to measure distances. However, the Received Signal Strength Indication (RSSI) provides some distance information that can nevertheless be used, although with a priori very limited accuracy. The RSSI is generally considered to be unreliable for distance evaluation, difficult to model and very sensitive to the environment (due to shading effect, reflections, lack of polarization of antennas), even if, in radio waves based triangulation methods, analytical and empirical methods have been proposed to take into account the delicate problem of reflections in indoor environment [8]). For radars, considering waves that make a round trip between the radar and the objet, the received power $P_r$ is usually written in terms of the transmission power $P_t$ as:

$$P_r = P_t \frac{G^2 \lambda^2 \sigma}{(4\pi)^3 R^4},$$

(2)

where $G$ is the antenna gain, $\sigma$ the radar cross section (reflection) of the target, and $\lambda$ the wavelength.

For a transmitted signal $s_t(t) = \cos(2\pi f_c t)$, neglecting the phase term, the received signal can be written as $s_r(t) = \alpha \cos(2\pi (f_c + f_d)t)$ where $\alpha$ is a distance dependent attenuation factor deduced from Eq. (2).
In the sensor, the received signal is mixed with the emitted signal (c.f. Fig. 2) giving:

\[ s_{\text{mixed}}(t) = \cos(2\pi f_c t) \alpha \cos(2\pi (f_c + f_d) t) \]

\[ = \frac{\alpha}{2} \cos(2\pi (2f_c + f_d) t) + \frac{\alpha}{2} \cos(2\pi f_d t) \]  

(3)

Filtering the result through a low-pass filter provides a signal

\[ s(t)_{IF} \propto \frac{\alpha}{2} (\cos(2\pi f_d t)) \]  

(4)

which permits to estimates the frequency \( f_d \), and whose amplitude is directly proportional to the received power and can therefore be used to estimate a distance.

Rather than using the level of total energy received, we propose to use the magnitude of the predominant frequency in the signal, which likely corresponds to the direct path.

Eventually, the distance \( R \) is recovered from this magnitude, assuming that the target cross section is constant during movement and magnitude follows a free field \( k/R^4 \) model (cf. (2)). Since no emitter or receiver is carried, this method is naturally immune to shadowing or antenna polarization alignment problems from which RSS techniques usually suffer.

2 Real Time Localization Method

The experimental setup consists of a set of static sensors (at least two orthogonal sensors) as shown in Fig. 3. These sensors use *patch-plane antennas* and are not very directional, they have an attenuation of less than 3dB at ±60° on the horizontal plane. It is therefore advisable to move them a few metres away from the working surface to cover it completely without introducing too much attenuation linked to directivity.

The Doppler output of each sensor is connected to a suitable amplification circuit (about 60 dB) including a 5 Hz-900 Hz pass-band filter (corresponding to
a maximum speed of 20 km/h). The output signals of the sensors are sampled and an autocorrelation is performed to determine the doppler frequency in the noisy signal. The magnitude is computed using a FFT.

In order to increase the precision of the system, the user can be furthermore equipped with an Inertial Motion Unit (IMU) that combines data from an accelerometer, a gyroscope and a magnetometer to estimate his/her orientation. We use an IMU composed of the low-cost MEMS (Microelectromechanical systems) sensor TDK-Inversense MPU9250 connected to a microcontroller running the Magdwick data fusion algorithm [9]. Such a device can provide orientation information with an accuracy of about 3–5°. It is a small wireless device (the size of a matchbox), that can be worn on the belt.

In the method described below, it is assumed that the user is moving in the direction of the sagittal plane (i.e. orienting himself in his direction of travel). The IMU also helps in suppressing the forward-backward ambiguity which exists when using the doppler radars alone, at least in their most simple use.

We aim at developing an algorithm for estimating the position of the subject. In that respect several difficulties need to be solved:

- Radars sensors provide highly noisy and often unusable (no sharp peaks in the spectrum) or missing measurements.
- It is impossible to distinguish motionless situations from those with no measurement (out-of-range).
- The measurement noise is not gaussian and hard to model.

To address these issues, we have developed a localization algorithm based on the particle filter (PF) method. PFs are algorithms for estimating the state of a dynamic system using Monte-Carlo methods. The PF are suitable for (strongly) non-linear models, non-Gaussian measurement noise and incomplete measurements. The particle filter algorithm is given in Algorithm 1 below.
Algorithm 1: Doppler Radar particle filter algorithm.

Result: Particle filter
(Initialization) Random creation of a set of particles representing the possible states including speed and position

for $k = 0$ to $Max$ do
  – For all particles: prediction of next particle state assuming a constant velocity
  – Measure sensors radial velocity, distance deduce from RSS and IMU orientation.
    • Identify static target situation (sub-threshold velocity and RSSI for all sensors)
    • Discard inconsistent measurements;
  – For all particles: Updating the particle weight taking into account the measurement;
  – Removal of Small Particles and resampling;
  – Calculation of the estimate (using a weighted average);

end

3 Results

3.1 Distance Estimation Accuracy

We evaluate the ranging accuracy using the magnitude of the Doppler signal alone in the case of a displacement in the direction of the axis of the sensor as well as in the case of a displacement in the orthogonal direction. First, a subject is walking back and forth towards the sensor at roughly constant walking speed. Figure 4-left compares the actual distance to the measured one. We observe that the dispersion of data increases with the distance, but we can see that the $k/R^4$ model provides nevertheless a realistic estimation.

Fig. 4. Left : Measures of distance during a series of movements in the sensor axis. The blue dotted line represent the real distance - Three right figures : Dispersion of distance measurement during a series of movements orthogonal to a sensor, left at 2 m, center at 3.5 m, right at 4.5 m.

We report in Fig. 4-right the distance measurements when moving in a direction orthogonal to the sensor. In this case, the model is suitable as well, but the dispersion increases sharply as the distance increases (Table 1).
Table 1. Typical ranging error while moving at different distances

|         | 2 m | 4 m | 6 m |
|---------|-----|-----|-----|
| RMS Error (m) | 0.62 | 0.7 | 0.77 |

3.2 Localization with a Particle Filter

We have implemented the device described in Fig. 3 in a surface area of $8 \times 8 \text{m}$. Tests are conducted with a single person walking (speed from 0.5 to 1.5 m/s) in this area.

Tracking on Different Courses. In order to show the tracking capabilities of the system, we have performed different types of displacements. Some are visible in Fig. 5.

![Circular movement](image1)
Circular. Velocity + RSS fusion

![Cross-shaped movement](image2)
Cross-shaped. Velocity + RSSI fusion

![S-shaped movement](image3)
S-shaped. Velocity + RSSI fusion

Circular movement with round trip

Cross-shaped movement

S-shaped movement

These different movements include smooth and continuous movements as well as abrupt changes of direction, round and long trips. Theses tests were carried out using radar RSS and velocity data but also incorporating the orientation of the person given by the IMU.
During our tests, after initial convergence, the maximum error remains less than 1.5 m while the average error is around 0.5 m. In most cases, the IMU allows to improve the quality of positioning by significantly smoothing trajectories, which is useful for the audio guidance applications we develop.

**Sensor Fusion Efficiency.** Figure 6 illustrate localization on a circular course using RSSI only, velocity only and data fusion. Localization using velocity can be quickly affected by drift while RSSI alone presents a rather erratic trace due to the imprecision of the measurements.

![Typical fusion result for an circular course](image)

**Fig. 6.** Typical fusion result for an circular course

On a circular type course of about ten revolutions, including U-turns at not constant speed, the average error was about 0.4 m and 0.9 m maximum using the velocity/distance/IMU fusion. Without the IMU, the average error is about 0.7 m and 1.3 m maximum (Fig. 7).

![Tracking during a long circular course](image)

**Fig. 7.** Tracking during a long circular course

In all experiments, the accuracy is limited by the error in the estimation of the distances and the velocities. Nevertheless, it is noticeable that no significant drift is observed even in experiments with many turns in circular courses.
4 Conclusion

Our experiments have shown that the fusion of RSSI and velocity data allows for the use of very low cost Doppler radar sensors for localization applications that do not require high accuracy. Indeed, RSSI measurements permit to limit the position drift that would be observed with velocity measurements alone.

The limited range (about 10 m) of the system is the main issue of this technology. Although limited, the accuracy could be sufficient for guidance applications. We plan to investigate further with more sensitive sensors in particular to use them for applications in guiding visually impaired people for indoor sport activities as we already did with Ultra-Wideband or RTK-DGNSS outdoor [1].

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