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RADIO AND IMU BASED INDOOR POSITIONING AND TRACKING

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ABSTRACT

Navigation using inertial measurement units (IMUs) is an interesting area of research. Due to the low cost hardware and simple implementation, the approach looks very attractive. But the performance of the IMUs to provide sub-meter accuracy over a longer period of time is still not sufficient, so different approaches have been adopted to increase the performance at the cost of extra hardware and/or infrastructure. Our solution is based on the use of already existing radio infrastructure, where amplitude and phase variations in a received radio signal at the user terminal is used together with the IMU to do a tightly coupled estimation of navigation and radio signal multipath components. The results show that the approach has the potential to enhance the performance of IMU based navigation significantly.

Index Terms— IMU, Sensor Fusion, Particle Filter, Positioning, Angle-of-Arrival, Channel Estimation

1. INTRODUCTION

Dead reckoning navigation using low cost Inertial Measurements Units (IMU) is a tempting navigation solution due to its simplicity. Cheap and small devices and no interaction with any other hardware are among the benefits of this solution. By combining an IMU with a moving device, and implementing time integration of the signals could provide a nice and reliable navigation solution. However, due to accelerometer noise and gyroscope drift, the position estimation errors will grow unboundedly with time. This serious problem has led to a number of different solutions where the IMU has been integrated with other hardware such as UWB transceivers [1], GPS receivers [2], cameras [3] etc. to track moving object with high resolution. The drawbacks with these solutions are obvious. UWB transceivers need extra hardware to be installed and calibrated, GPS receivers need GPS signal coverage and navigation using cameras needs clear sight and the possibility to find reference points.

Today, the cellular networks coverage is usually very good in urban areas. A cellular network is built of base stations being placed to give good signal strength, both outdoors as well as inside buildings. Today, the network is already being used for positioning purposes, but the accuracy and resolution

regarding positioning are limited due to fading and bandwidth limitations. Directional based positioning is not used since most hand held devices today has a single antenna. However, the combination of IMU and a single antenna can be used to create a synthetic array antenna. If the position of the single antenna is known, an array antenna with a stochastic form is created.

This paper aims to present and explain a method using angle-of-arrival (AoA) information at the handset to limit the position estimation errors. The solution presented here is a tightly coupled solution using channel estimates from a synthetic array antenna and a particle filter to solve the Bayesian estimation problem. The result is a tracker of both position and orientation. The main advantage over previous navigation solutions is that for cell phones there is no need for additional hardware, and it provides a solution that can work where GPS coverage is bad. A simplified schematic drawing is shown in Fig. 1.
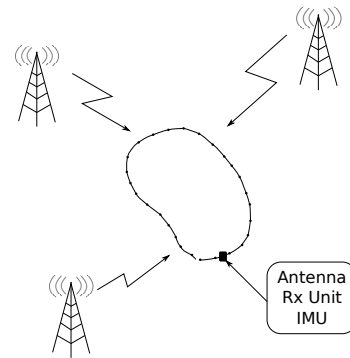

Fig. 1. Measurement scenario: Radio receiver and IMU moving in a radio environment.

To the authors' knowledge there are no such attempts in the literature today. [4] describes a solution where the MUSIC algorithm is used to find the direction to an interfering signal with the purpose to enhance GNSS navigation by cancelling the interference.

2. PROBLEM FORMULATION

The IMU consists of a 3-axis accelerometer, gyroscope and magnetometer that is commercially available. The device used here is a Phidget-1056 [5]. The gyroscope, accelerometer and magnetometer are integrated on a single device and samples are synchronized by the hardware which facilitates further signal processing. In the setup, measurements from the magnetometer are not used. The gyroscope measures the rotational speed ω^b of the device while the accelerometer measures the external acceleration acting on the device, consisting of both gravity $\bar{g}$ and acceleration caused by movement a^b. These measurements are resolved in the navigation frame of the IMU which is different from the navigation frame of the room. The former is called the body frame and the latter is named the world frame. A visualization of two navigation frames are shown in Fig. 2. Signals resolved in the body frame are denoted with superscript ^{b} and equivalently with ^{w} for the world frame signals.
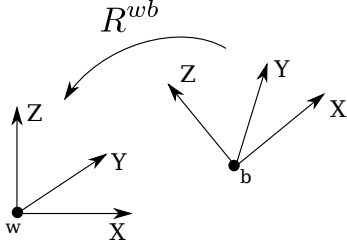

Fig. 2. World and body navigation frames. w denotes world navigation frame and the body frame, denoted b, is shown rotated and displaced from the world frame. R^{wb} denotes the rotation matrix transforming the body frame coordinates to world frame coordinates.

The center of the body frame is the origin of the three accelerometer axis and hence moving as the IMU is moved in the room. The center of the world frame is an arbitrary point in the room defined as origin and this coordinate frame is stationary. The displacement of the device from the world frame is the position estimated while the orientation is the rotation of the body frame with respect to the world frame.

The IMU can in theory be used to calculate a position relative to the world frame using dead reckoning. Such a system is presented in Fig. 3.
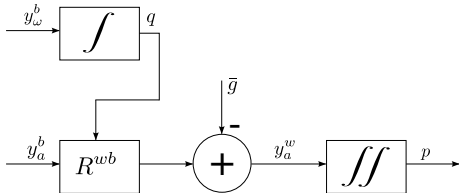

Fig. 3. Dead reckoning navigation using standalone IMU.

This procedure is simple, the signal from the gyroscope is integrated to find the orientation of the device. With the orientation, the signals from the accelerometer can be rotated and gravity subtracted. The residual is finally double integrated to retrieve the position estimate. The issues with this solution is obvious, measurement noise from the gyroscope and accelerometer will be integrated and cause the position to quickly drift away. Hence, the signal from the IMU needs to be calibrated to get a working solution.

3. MODELLING

The signals from the IMU and the radio receiver has to be modeled using known as well as unknown parameters.

3.1. IMU

The kth sample from the accelerometer $y_{a,k}$ and the gyroscope $y_{\omega,k}$ is modeled as:

$$y_{a,k}^b = a_k^b + \bar{g}^b + e_{a,k}^b \tag{1}$$

$$y_{\omega,k}^b = \omega_k^b + e_{\omega,k}^b, \tag{2}$$

where $y_{a,k}^b \in \mathbb{R}^3$ and $y_{\omega,k}^b \in \mathbb{R}^3$ [6]. a^b is the acceleration caused by movement, $\bar{g}$ is the gravity vector, ω^b is the rotational speed of the device and e_a^b and e_ω^b are independent measurement noise.

3.2. Radio environment

The transmitted radio signal is assumed to be a narrowband single sinusoid, as e.g., found in the GSM frequency synchronization channels. Other signals are of course possible, but note that the technology does not require any delay information. There are scatterers in the environment which scatters the radio signal and create multipath components at the receiver. Each multipath component is modeled to have independent and unknown amplitude and initial phase offset. If n scatterers are assumed to be far away, the signal at the receiver can be written as

$$y_{r,k} = \sum_n \alpha_{n,k} e^{i\beta(cos(\theta_n)p_{x,k} + sin(\theta_n)p_{y,k}) + \varphi_k} + e_{r,k} \tag{3}$$

where $\beta = \frac{2\pi}{\lambda}$, θ_n is a fixed, unknown, angle to the scatterer, α_n is an unknown but constant amplitude and finally $p_{x,k}$ and $p_{y,k}$ is the x and y position at sample k respectively. Note that no information about the z-axis is assumed to be given by the radio measurement.

3.3. Dynamic model

The orientation of the device is described by quaternions [7]. The representation with quaternions is superior compared to

other representations since it does not have any singularities. The dynamic equations for the quaternions are not derived here but merely summarized, for further derivations see [7]. The update equation for the quaternion q_k is given by

$$q_{k+1} = e^{-\frac{h}{2}S(y^b_{\omega,k})}q_k, \tag{4}$$

where h is the sampling interval and and $S(y^b_\omega)$ is given by

$$S(y^b_\omega) = \begin{bmatrix} 0 & -\omega^b_x & -\omega^b_y & -\omega^b_z \\ \omega^b_x & 0 & \omega^b_z & -\omega^b_y \\ \omega^b_y & -\omega^b_z & 0 & \omega^b_x \\ \omega^b_z & \omega^b_y & -\omega^b_x & 0 \end{bmatrix}. \tag{5}$$

The measurements in the body frame are transformed to the world frame by

$$y^w_{a,k} = R^{wb}(q_k) \cdot y^b_{a,k} - \bar{g}, \tag{6}$$

where $R^{wb}(q_k)$ is the rotation matrix and is given by

$$R^{wb}(q_k) = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2q_1q_2 + 2q_0q_3 & 2q_1q_3 - 2q_0q_2 \\ 2q_1q_2 - 2q_0q_3 & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2q_2q_3 + 2q_0q_1 \\ 2q_1q_3 + 2q_0q_2 & 2q_2q_3 - 2q_0q_1 & q_0^2 - q_1^2 - q_2^2 + q_3^2 \end{bmatrix}. \tag{7}$$

The velocity and position is described with the ordinary dynamic equations for rigid body models. The state model can be summarized as

$$p_{k+1} = p_k + hv_k + \frac{h^2}{2}y^w_{a,k} \tag{8}$$

$$v_{k+1} = v_k + hy^w_{a,k}, \tag{9}$$

where $p_k \in \mathbb{R}^3$ and $v_k \in \mathbb{R}^3$.

The radio signal amplitude and phase are modeled as independent random walk processes, since these parameters are independent. The scatterer-receiver angle is also modeled as independent random walk processes.

$$\theta_{k+1} = \theta_k + he_1 \tag{10}$$

$$\alpha_{k+1} = \alpha_k + he_2 \tag{11}$$

$$\varphi_{k+1} = \varphi_k + he_3 \tag{12}$$

The above dynamic models can finally be collected together in a sensor fusion framework with the derived process dynamics. A state vector collecting the unknowns is introduced as

$$\hat{x}_k = \{p_k \quad v_k \quad q_k \quad \theta_k \quad \alpha_k \quad \varphi_k\} \tag{13}$$

and $\hat{x}_k \in \mathbb{R}^{10+3n}$ where n is the number of scatterer.

3.4. Sensor fusion

With the dynamic model derived in section 3.3, the measurements from the IMU and the radio signal are hereby tightly coupled to estimate the state vector. Since the model includes both linear and nonlinear states as well as a nonlinear measurement equation, a particle filter was chosen to solve the state estimation problem [8]. The particle filter can be summarized in two steps, first the states are updated according to the model and the process noise, and then the measurement is received and the states calculated before are evaluated to the measurements. The tuning parameters of the filter is the process noise, the measurement noise and the number of particles. The filter also requires an initial guess of the state vector.

4. EXPERIMENT

An IMU such as described in section 2 and a monopole receiver antenna was attached to a stick mounted on a tripod as shown in Fig. 5. The stick can be rotated around the pivot point giving a circular movement following a fixed trajectory. Three scatterers are realized with three transmit antennas transmitting at the same frequency. The transmit frequency used in the measurements is 1795 MHz. The measurements were made on a roof with clear line of sight between transmitters and receiver antenna and no reflecting/scattering objects nearby, see placement in Fig. 4. The radio signal is received with a SNR of about 30 dB. The received radio signal is sampled at 50 kHz in the baseband while the IMU data was recorded at 250 Hz. A signal recording application on a software defined radio from National Instruments was developed; allowing synchronous recording of radio signal and IMU measurements. The initial distribution for the amplitude α was chosen as a gaussian while the phase offset φ and receiveing angle θ where initialized with uniform distributions. In the case of θ the distribution was $\pm 10°$ from the estimated values. For φ the distribution was $[0 : \pi]$. The number of particles used was 2500.
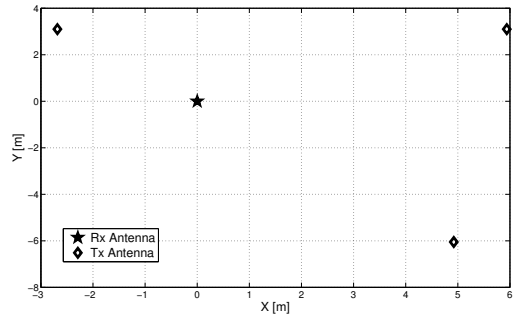
Fig. 4. Tx and Rx antenna positions in the experiment setup.

5. RESULTS

Fig. 6 shows the trajectory in the XY-plane after the signals were fused using the particle filter. The filter is initilialized to
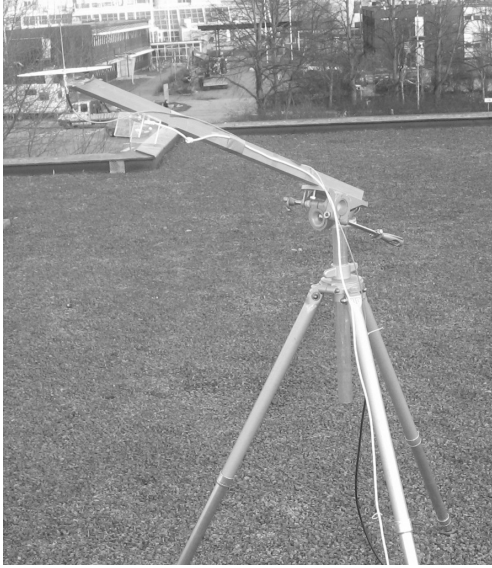
Fig. 5. The experiment setup. The monopole antenna can be seen to the upper left in the figure and the IMU is mounted upside-down on the stick.

Fig. 6. Trajectory in XY-plane. The avgerage particle is indicated with the solid black line, the estimated true trajectory is the dashed line. The particles can be seen at $(0,0)$ where the device it kept at rest for a short period of time. When the movement starts, the clouds of particles converges quickly covered by the average.

origin. Before the movement starts the IMU is kept static for about 3-4 seconds and the following circular movement took about 2 seconds. The uncertainty in the position is increasing before the movement starts which is due to integration of the white noise present in the IMU measurments. When the movement starts, there is a good alignment with the true trajectory.

6. SUMMARY

This article describes an approach to increase the accuracy achieved by dead reckoning using low cost IMU:s aided by radio signal information. The experiment calls for further studies since many questions are left unanswered; future work includes how to deal with scattering of radio signals in indoor environments with more multipaths components, initialization of the filter and influence of human interaction in the radio environment. Also the limits of performance taking realisable imperfections into account needs to be investigated.

7. ACKNOWLEDGEMENT

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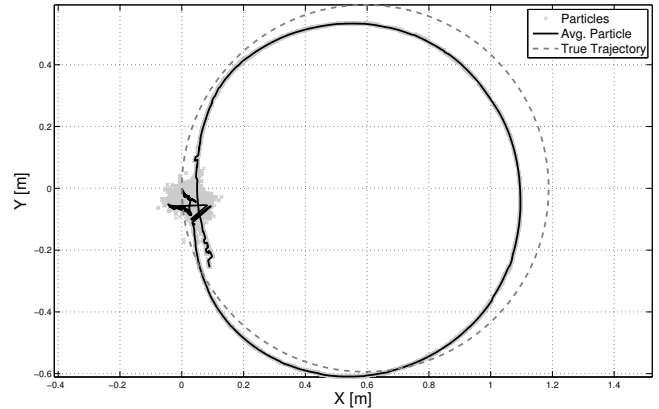
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