

SKM: low-cost precise positioning based on TDoA UWB and MEMS IMU

Nadezhda Kukovyakina, Dmitry Tsaregorodtsev, Roman Kulikov (member IEEE)

National Research University MPEI, Moscow, Russia

ABSTRACT

The UWB technology is becoming de-facto standard solution for indoor positioning, localization and navigation with high accuracy requirements. The theoretical explanation was known far ago, UWB signals have ultra-short auto-correlation time so it is much more suitable for multipath mitigation which is inherent for indoor applications. Common approach is based on network of fixed anchors and number of mobile tags which measured some combination of time of arrival of signals to compute distances (or some function of distances like distances differences) between them and transform it to local coordinates (localization, position) in real time. Accurate UWB measurement requires clear line-of-sight between each tag and anchors. But it could be difficult to provide clear line-of-sight in real environment. So, the outages of measurements are possible during working session. There are number of approaches to reduce harmful effect of line-of-sight disturbance such as 1) increasing number of anchors, 2) using additional processing for excluding corrupted measurements, 3) coupling with other technology (e.g. IMU), 4) cooperative navigation within multiple tags, 5) advanced filtering. Regarding to competition conditions we offer positioning system focusing on 2), 3) and 5).

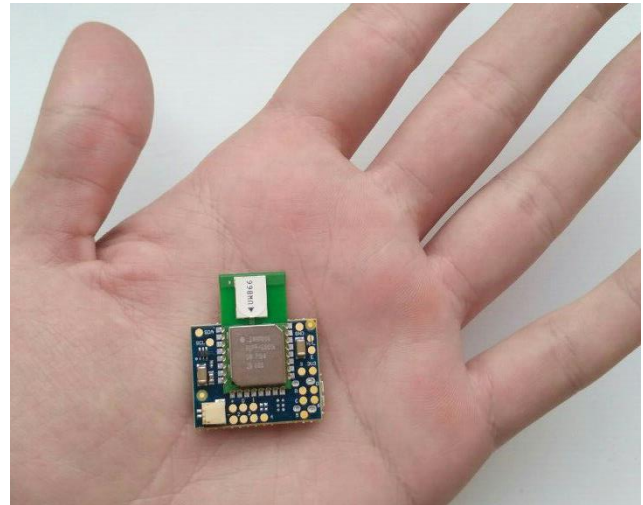
Keywords: indoor, localization, navigation, positioning, real-time, UWB, TDoA, IMU, coupling, advance filtering.

1 INTRODUCTION

There are some alternative technologies for indoor positioning such as ultrasonic, lidar, UWB radio, RFID/WiFi/Bluetooth trilateration and fingerprinting, inertial, magnetic. Lidar is accurate, but very expensive and the most fragile due to containing of moving parts. Ultrasonic is sufficiently accurate but have too large delay and too low update rate. UWB radio could provide moderate update rate and low latency, but it has large noise error. RFID/WiFi/Bluetooth trilateration and fingerprinting provide indoor positioning with no additional customer's hardware except a convenient smartphone but these technologies lack accuracy and provide relatively slow update rate. Magnetic technology is very precise and fast, but it could be easily implemented only within very limited space (usually table-scale area for precision gesture/finger-tracking). Inertial technology is very fast and relatively low-noisy, but its drift leads to unlimited increasing of systematic error. So, no one cost-effective technology is suitable for precise, reliable and fast positioning in standalone mode.

In common theory of information processing the coupling (fusing) of different sensors is used for decades to overtake similar problems [1]. Mostly radio and inertial sensors are coupled to obtain estimations with high update rate, low noise and zero systematic error. Coupling requires more sophisticated processing software, but allows usage of cheap low-quality and noisy sensors.

We offer the 3D positioning system based on UWB radio ranging coupled with inertial measurements. Anchors and tag are LPS2 mini modules produced by Loligo Electronics [5]. LPS2 mini module is based on Deca Wave DWM1000 UWB radio-ranging module [4], IMU, proprietary control&interface scheme and proprietary firmware (picture 1).



Picture 1. Anchor and/or tag of positioning system.

The positioning system contains number of fixed anchors and unlimited number of tags. The Reverse Time Difference of Arrival (RTDoA) mode is realized in the system. In this mode anchors are synchronized by master-anchor wirelessly. Each anchor emits its signal at corresponding moment within each time-slot; length of single time slot which contains signals of 8 anchors is 40 ms. Tag receives set of anchors' signals and measures time differences of arrival moments. So, every 40 ms there is set of measured differences of arrival time of all radio-visible anchors. These measurements are transferred to USB-micro port of LPS2 mini. Besides that the inertial measurements are transferred to USB-micro port each 10 ms.

We collect UWB and IMU data from USB-port of LPS2 mini and couple them in PC. The coupled system provides cost-effective, precise, fast and reliable positioning of unlimited number of users even in difficult environment.

In the section 2 the models of radio and inertial measurements and state vector are presented, as well as the filter, the estimate of error based on computer modelling are pointed.

2 MODELS AND ALGORITHM

Advantage of sensors coupling could be achieved only if sensors have different natures of their errors, at that, the bigger difference the bigger advantage is. Fortunately, the difference between radio-ranging error and inertial error is significant. For 6 degree of freedom (6DoF) positioning the dependence between navigation elements (vector of coordinates and orientation as well as vectors of velocity, acceleration and angular speed) is highly nonlinear. So, the nonlinear extrapolation and filtering is required.

* nadya.3k@gmail.com
tsdv95@mail.ru
kulikovRS@mpei.ru

2.1 Measurement models

The radio-ranging sub-system provides vector estimation of 3D coordinates within local XYZ coordinate frame which is attached to the gaming room. There is almost no systematic error but there is relatively high noise error:

$$\mathbf{r}_k = [x \ y \ z]^T_k + \mathbf{n}_k = \mathbf{x}_k + \mathbf{n}_k, \quad (1)$$

where $k = 1, 2, 3, \dots$ is discrete time index; T denotes transpose operation; \mathbf{n} is 3D vector of independent white gaussian noises with zero average and dispersion matrix $\mathbf{R}_r = \text{diag}([\sigma_x^2 \ \sigma_y^2 \ \sigma_z^2])$ which components depend on geometry of radio-anchors.

The inertial sub-system provides vector estimation of accelerations and angular speeds within body's RPY (roll-pitch-yaw) coordinate frame after subtraction of gravity vector which is considered known and constant. There are systematic error and relatively low noise error:

$$\mathbf{u}_k = \begin{bmatrix} \mathbf{a}_k \\ \boldsymbol{\omega}_k \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_{a_k} \\ \boldsymbol{\varepsilon}_{\omega_k} \end{bmatrix} + \begin{bmatrix} \mathbf{n}_{a_k} \\ \mathbf{n}_{\omega_k} \end{bmatrix}, \quad (2)$$

where \mathbf{a}_k is vector of real acceleration; $\boldsymbol{\omega}_k$ is vector of real angular rates; \mathbf{n}_{a_k} and \mathbf{n}_{ω_k} are vectors of independent white gaussian noises of accelerometer and gyro measurement respectively with zero average and dispersion matrices $\mathbf{R}_a = \text{diag}([\sigma_{a_n}^2 \ \sigma_{a_n}^2 \ \sigma_{a_n}^2])$ and $\mathbf{R}_\omega = \text{diag}([\sigma_{\omega_n}^2 \ \sigma_{\omega_n}^2 \ \sigma_{\omega_n}^2])$ respectively; $\boldsymbol{\varepsilon}_{a_k}$ and $\boldsymbol{\varepsilon}_{\omega_k}$ are vectors of biases of accelerometer and gyro respectively, they may be represented as quazi-constant unknown stochastic vector values (more simple approach) or as slow wiener stochastic processes (more accurate approach):

$$\boldsymbol{\varepsilon}_{a_k} = \boldsymbol{\varepsilon}_{a_{k-1}} + \mathbf{b}_{a_k}, \quad (3)$$

$$\boldsymbol{\varepsilon}_{\omega_k} = \boldsymbol{\varepsilon}_{\omega_{k-1}} + \mathbf{b}_{\omega_k}, \quad (4)$$

where \mathbf{b}_{a_k} and \mathbf{b}_{ω_k} are vectors of independent white gaussian dynamic noises with zero average and dispersion matrices $\mathbf{Q}_a = \text{diag}([\sigma_a^2 \ \sigma_a^2 \ \sigma_a^2])$ and $\mathbf{Q}_\omega = \text{diag}([\sigma_\omega^2 \ \sigma_\omega^2 \ \sigma_\omega^2])$ respectively

When using low-cost MEMS IMU, the influence of axis non-orthogonality, nonlinearity and error of axis scaling are much less than influence of bias and noise. So, only bias and noise are considered in inertial measurements model.

It is important to note that update rate of radio-ranging coordinates is less than that of inertial. It should be considered when designing extrapolating and filter algorithm.

2.2 State Vector and Filter

The state vector contains the following sub-vectors: XYZ coordinates \mathbf{x} , XYZ projections of velocity \mathbf{V} , orientation quaternion \mathbf{q} , biases of accelerometer $\boldsymbol{\varepsilon}_a$ and gyro $\boldsymbol{\varepsilon}_\omega$:

$$\mathbf{s}_k = [\mathbf{x}^T \ \mathbf{V}^T \ \mathbf{q}^T \ \boldsymbol{\varepsilon}_a^T \ \boldsymbol{\varepsilon}_\omega^T]^T_k. \quad (5)$$

The nonlinear connections between components of state vector and inertial measurements (which are considered approximately known with accuracy up to noises \mathbf{n}_{a_k} and \mathbf{n}_{ω_k}) are the following:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{V}_{k-1}T + \mathbf{C}(\mathbf{q}_{k-1})(\mathbf{u}(1:3)_k - \boldsymbol{\varepsilon}_{a_{k-1}})T^2/2, \quad (6)$$

$$\mathbf{V}_k = \mathbf{V}_{k-1} + \mathbf{C}(\mathbf{q}_{k-1})(\mathbf{u}(1:3)_k - \boldsymbol{\varepsilon}_{a_{k-1}})T, \quad (7)$$

$$\mathbf{q}_k = \mathbf{q}_{k-1} \otimes \Delta_k, \quad (8)$$

$$\Delta_k = \begin{bmatrix} \cos(\|\boldsymbol{\rho}_k\|/2) \\ \frac{\rho(1)_k}{\|\boldsymbol{\rho}_k\|} \sin(\|\boldsymbol{\rho}_k\|/2) \\ \frac{\rho(2)_k}{\|\boldsymbol{\rho}_k\|} \sin(\|\boldsymbol{\rho}_k\|/2) \\ \frac{\rho(3)_k}{\|\boldsymbol{\rho}_k\|} \sin(\|\boldsymbol{\rho}_k\|/2) \end{bmatrix}, \quad (9)$$

$$\boldsymbol{\rho}_k = (\mathbf{u}(4:6)_k - \boldsymbol{\varepsilon}_{\omega_{k-1}})T, \quad (10)$$

$$\mathbf{C}(\mathbf{q}) = \begin{bmatrix} q_1^2 + q_2^2 - q_3^2 - q_4^2 & 2(q_2q_3 - q_1q_4) & 2(q_1q_3 + q_2q_4) \\ 2(q_2q_3 + q_1q_4) & q_1^2 + q_3^2 - q_2^2 - q_4^2 & 2(q_3q_4 - q_1q_2) \\ 2(q_2q_4 - q_1q_3) & 2(q_1q_2 + q_3q_4) & q_1^2 + q_4^2 - q_2^2 - q_3^2 \end{bmatrix}, \quad (11)$$

where $\mathbf{C}(\mathbf{q})$ is matrix of transition between RPY frame and XYZ frame; \otimes denotes vector product of quaternions; $\boldsymbol{\rho}_k$ is rotation vector; T is update period of inertial measurements.

Dynamic model (3-4), (6-11) doesn't reckon rotating of Earth because it's influence is much less than influence of biases and noises of low-cost IMU.

Nonlinear filter should estimate the state vector based on dynamic model (3-4), (6-11) and measurement model (1). At discrete moments of getting inertial measurements (2) only state vector extrapolation stage is conducted with respect to dynamic model (3-4), (6-11). At the more rarely moments of receiving radio-ranging measurements the state vector correction stage is conducted.

Different nonlinear approaches could be used to design filter such as extended Kalman filter [1], unscented filter [2] and particle filter [3]. In our current work we use the SIR version of particle filter.

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