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doi:10.15199/48.2019.11.36

Personal navigation system using ultrawideband technology

***Abstract**. This paper describes a high-accuracy personal navigation system based on measurements of distances between ultrawideband (UWB) radio modules. The paper contains a description of the physical model of the presented system. Furthermore, positioning algorithms implemented in the proposed system are discussed with emphasis on the Extended Kalman Filter. Subsequently, the process of experiments is described, and chosen results are given.*

***Streszczenie.** W artykule przedstawiono system nawigacji personalnej o wysokiej dokładności pozycjonowania, oparty na pomiarach odległości pomiędzy modułami ultraszerokopasmowymi (UWB). Artykuł zawiera opis fizycznego modelu systemu. Ponadto, omówione zostały algorytmy pozycjonujące zaimplementowane w systemie, przy czym najwięcej uwagi poświęcono rozszerzonemu filtrowi Kalmana. Następnie, omówiono przebieg badań oraz podano ich wybrane wyniki. (**System nawigacji personalnej wykorzystujący technikę ultraszerokopasmową**).*

Keywords: personal navigation system, ultrawideband technology, positioning, Extended Kalman Filter.
Słowa kluczowe: system nawigacji personalnej, technika ultraszerokopasmowa, pozycjonowanie, rozszerzony filtr Kalmana.

Introduction

Advantages of ultrawideband (UWB) signals have made them applicable in many fields of technology. Due to many useful features they are commonly used in navigation [1,2]. The ultrawideband technology allows to achieve a very high accuracy of distance measurements, which positively affects the accuracy of positioning. Moreover, UWB signals are to some extent capable of penetrating obstacles, which enables positioning in closed spaces, such as buildings [1]. They are also highly immune to interferences from other sources of electromagnetic signals [3]. Their low-power and spread-spectrum signals are difficult to detect and localize [4,5] which may be an important feature if the personal navigation system is used by the military or other services.

The most popular personal navigation systems are often based on GNSS systems, especially GPS [6,7]. Receivers of this system are commonly applied in portable devices and allow to determine the position of both vehicles and pedestrians. However, one of the biggest disadvantages of such systems is their limited capability of positioning inside buildings. In such conditions, Inertial Navigation Systems (INS) can be used, which are also frequently applied for navigational purposes [8,9]. Inertial Measurement Unit (IMU), which consists of accelerometers and gyroscopes, carried by the user allows to determine a user's position in almost any conditions. In such solutions, however, increasing errors of user's position estimation occur. The values of these errors depend on the technology that was used to make the measurement units and time. To reduce the errors, the use of expensive IMUs or integration of INS with other navigation systems is required.

In this article, a high accuracy positioning system, using distance measurements between UWB radio modules to determine user's position is presented.

Description of the system

The developed system uses PulsON 440 UWB radio modules, which work in a frequency range between 3.1 and 4.8 GHz [10]. One of them is a part of a mobile unit, carried by the user, while the others work as components of base stations (beacons), which are deployed around the area in which navigation should be provided. The UWB modules are responsible for distance measurements, which are acquired using the Two-Way Time-of-Flight (TW-TOF) method for ranging [10].

The proposed system, presented in Fig. 1, is composed of four UWB beacons with known locations (X_i, Y_i) and one mobile unit which location (x, y) is unknown and must be estimated. The positioning is realized in a horizontal plane OXY only which is adequate for one-story buildings, but this simplifying assumption is easy to relinquish, and the system could easily be expanded to a full three-dimensional positioning version.

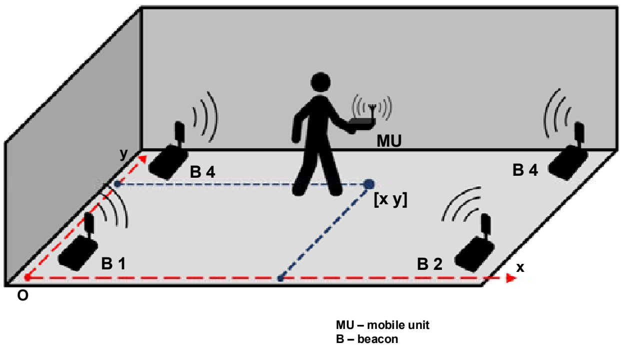

Fig.1. Composition and typical use of personal navigation system

The main components of the proposed system are presented in Fig. 2. As can be seen, the most complex element of the system is its mobile unit, which contains a UWB module, a microcontroller unit (MCU), a single-board computer (SBC) and an LCD screen. The beacons are simpler and contain only UWB modules and MCUs.

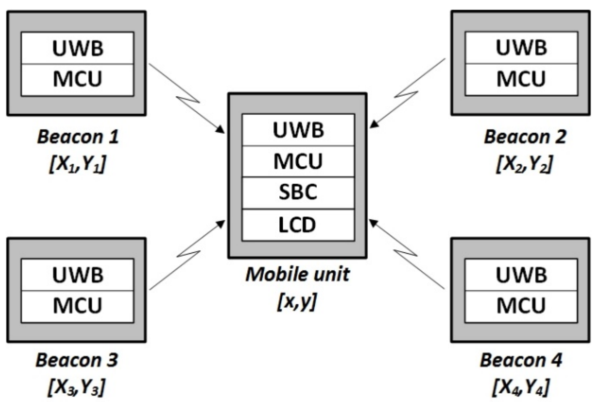

Fig.2. Structure of personal navigation system

The essential components of the mobile unit and the beacons are UWB modules. Their measurements of distances are transferred to the MCU of the mobile unit where they are processed with implemented positioning algorithms. The results of positioning are sent to data visualization system consisting of a single-board computer, which generates a graphical user interface (GUI), and an LCD screen. All the MCUs are additionally responsible for configuring UWB modules. The elements of the system are powered from attached power banks.

A physical model of the described system was manufactured, and it serves as a technology demonstrator for verifying the authors' concepts and implementing and testing navigation data processing algorithms. A photo of the system is presented in Fig. 3.

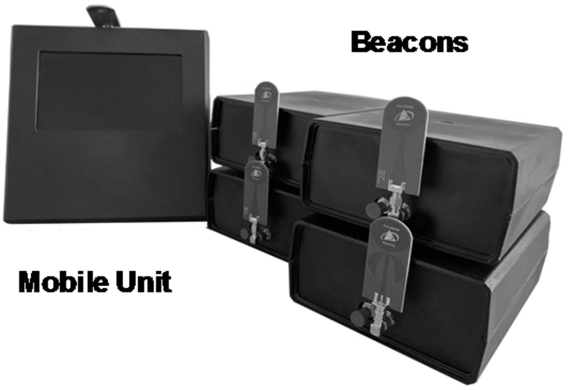

Fig.3. Photo of personal navigation system

Currently, a new version of our personal navigation system is in production. It has similar functionalities, but all the elements will be miniaturized and made waterproof, thus it will be capable of working in harsh environments.

Positioning algorithms

Positioning algorithms are essential in every navigation system. Various types of these algorithms are used, depending on the expected parameters of the system. The developed system uses two positioning algorithms which are an Extended Kalman Filter (EKF) [11,12,13] and an Ordinary Least Squares (OLS) algorithm [14]. The EKF belongs to a group of algorithms using a dynamics model describing user's motion. It is a modification of the traditional linear Kalman Filter (KF) which cannot be used in our system due to a non-linear observation model which describes a relationship between the measured ranges and the user's position.

What distinguishes the EKF from the KF is an observation matrix $\mathbf{H}$, the elements of which are partial derivatives of the measurements with respect to the state vector elements [15]. The values of these derivatives change with each measurement and they should be recomputed in every recursion of the algorithm. On the contrary, in linear KF the $\mathbf{H}$ matrix is directly known from the system's model and is not calculated by the filter itself. In the EKF the form of the equation responsible for correction is also different in comparison to the KF [12].

The dynamics model adopted in our algorithm is a PV (Position/Velocity) model, which is commonly applied for slowly moving objects, such as pedestrians [12,14]. The state vector (1) in the implemented algorithm consists of four variables (two for user's position and two for user's velocity) describing user's movement in the OXY plane.

(1) $$\mathbf{x} = [x \quad v_x \quad y \quad v_y]^T$$

The discrete dynamics model (2) is a linear difference equation which expresses a relationship between the user's position and velocity in kT and $(k+1)T$ moments [11].

(2) $$\mathbf{x}(k+1) = \mathbf{\Phi}(k+1,k)\mathbf{x}(k) + \mathbf{w}(k)$$

where: $\mathbf{\Phi}$ – transition matrix, $\mathbf{w}$ – vector of random process disturbances.

The dynamics model presented as a matrix equation is as follows:

(3) $$\begin{bmatrix} x(k+1) \\ v_x(k+1) \\ y(k+1) \\ v_y(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x(k) \\ v_x(k) \\ y(k) \\ v_y(k) \end{bmatrix} + \begin{bmatrix} w_x(k) \\ w_{v_x}(k) \\ w_y(k) \\ w_{v_y}(k) \end{bmatrix}$$

The covariance matrix $\mathbf{Q}$ of discrete disturbances of the process describes the influence of disturbances on the individual components of the user's position and velocity during the timestep T. It is a block-diagonal matrix, and its upper and lower 2×2 submatrices are calculated for X and Y coordinates respectively. The whole $\mathbf{Q}$ matrix used in our system is as follows:

(4) $$\mathbf{Q} = \begin{bmatrix} \frac{S_{v_x}T^3}{3} & \frac{S_{v_x}T^2}{2} & 0 & 0 \\ \frac{S_{v_x}T^2}{2} & S_{v_x}T & 0 & 0 \\ 0 & 0 & \frac{S_{v_y}T^3}{3} & \frac{S_{v_y}T^2}{2} \\ 0 & 0 & \frac{S_{v_y}T^2}{2} & S_{v_y}T \end{bmatrix}$$

where the elements S_{v_x} and S_{v_y} represent power spectrum densities of disturbing white noises for each axis [12].

The observation model describing a relationship between the state vector and the measurement vector is given as follows [11]:

(5) $$\mathbf{z}(k) = \mathbf{h}[x(k),k] + \mathbf{v}(k)$$

where: $\mathbf{z}$ – measurement vector, $\mathbf{h}$ – non-linear observation function, $\mathbf{v}$ – vector of measurement errors.

The elements of the measurement vector $\mathbf{z}$ represent distances between the mobile unit and the beacons. The $\mathbf{h}$ function describes the relationship between those distances and the positions of the mobile station and beacons. The adopted observation model is given as follows:

(6) $$\begin{bmatrix} d_1 \\ d_2 \\ d_3 \\ d_4 \end{bmatrix} = \begin{bmatrix} \sqrt{(X_1-x)^2 + (Y_1-y)^2} \\ \sqrt{(X_2-x)^2 + (Y_2-y)^2} \\ \sqrt{(X_3-x)^2 + (Y_3-y)^2} \\ \sqrt{(X_4-x)^2 + (Y_4-y)^2} \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix}$$

As it was already mentioned, the observation matrix $\mathbf{H}$, which must be computed in every recursion of the EKF algorithm, is composed of partial derivatives of the above $\mathbf{h}$ function with respect to the state vector elements, thus it is as follows:

(7) $$\mathbf{H} = \begin{bmatrix} \frac{\partial d_1}{\partial x} & 0 & \frac{\partial d_1}{\partial y} & 0 \\ \frac{\partial d_2}{\partial x} & 0 & \frac{\partial d_2}{\partial y} & 0 \\ \frac{\partial d_3}{\partial x} & 0 & \frac{\partial d_3}{\partial y} & 0 \\ \frac{\partial d_4}{\partial x} & 0 & \frac{\partial d_4}{\partial y} & 0 \end{bmatrix}$$

The above derivatives are given by (8) and (9):

(8) $$\frac{\partial d_i}{\partial x} = \frac{-(X_i - x)}{\sqrt{(X_i - x)^2 + (Y_i - y)^2}}$$

(9) $$\frac{\partial d_i}{\partial y} = \frac{-(Y_i - y)}{\sqrt{(X_i - x)^2 + (Y_i - y)^2}}$$

The above derived relationships allow to implement the EKF to the described personal navigation system. In Fig. 4, a block diagram of the EKF algorithm is presented [12].

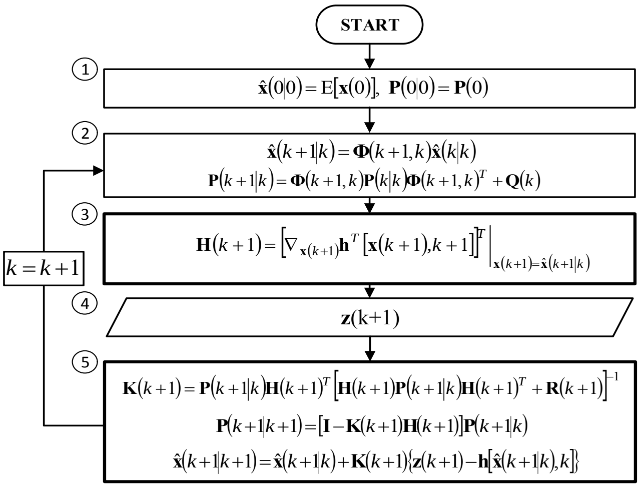

Fig.4. Block diagram of Extended Kalman Filter

The symbols used in the above diagram are as follows: $\mathbf{x}(0)$ – initial state vector, $\mathrm{P}(0)$ – initial covariance matrix, $\hat{\mathbf{x}}(k|k)$ – state vector estimated at the moment k, $\mathbf{P}(k|k)$ – covariance matrix of filtration errors at the moment k, $\hat{\mathbf{x}}(k+1|k)$ – predicted state vector at the moment $k+1$, $\mathbf{P}(k+1|k)$ – covariance matrix of prediction errors at the moment $k+1$, $\hat{\mathbf{x}}(k+1|k+1)$ – corrected state vector at the moment $k+1$, $\mathbf{P}(k+1|k+1)$ – covariance matrix of filtration errors at the moment $k+1$, $\mathbf{K}(k+1)$ – Kalman gains matrix at the moment $k+1$.

The presented algorithm consists of five phases: (1) initialization, (2) prediction, (3) calculation of the observation matrix $\mathbf{H}$, (4) acquisition of a new measurement vector and (5) correction. After the correction phase, the state vector containing information about the current position and velocity is forwarded for further processing.

In the proposed system, two positioning algorithms work parallelly. The second one is the Ordinary Least Squares algorithm. In this estimation method, an a priori user's position $(\hat{x}, \hat{y})$ is assumed. Then, distances between the assumed user's position and the beacons are calculated as follows:

(10) $$\hat{d}_i = \sqrt{(X_i - \hat{x})^2 + (Y_i - \hat{y})^2} \qquad i \in \{1,2,3,4\}$$

and a verification whether the calculated distances $\hat{d}_i$ are similar to the measured ones d_i is performed.

Next, corrections proportional to the discrepancies found $\hat{d}_i - d_i$ are calculated. In a matrix form they are as follows:

(11) $$\Delta\hat{\mathbf{x}} = (\mathbf{H}^{\mathrm{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathrm{T}}\Delta\mathbf{z}$$

where:

(12) $$\Delta\hat{\mathbf{x}} = \begin{bmatrix} \hat{x} - x \\ \hat{y} - y \end{bmatrix}$$

(13) $$\Delta\mathbf{z} = \begin{bmatrix} \hat{d}_1 - d_1 \\ \hat{d}_2 - d_2 \\ \hat{d}_3 - d_3 \\ \hat{d}_4 - d_4 \end{bmatrix}$$

Subsequently, the initially assumed user's coordinates are corrected by the elements of $\Delta\hat{\mathbf{x}}$ vector:

(14) $$\hat{x} \leftarrow \hat{x} - \Delta\hat{x} \qquad \hat{y} \leftarrow \hat{y} - \Delta\hat{y}$$

During the execution of the algorithm, the $\mathbf{H}$ matrix is calculated. It contains the same derivatives as the $\mathbf{H}$ matrix given by (7), however, it is not square:

(15) $$\mathbf{H} = \begin{bmatrix} \frac{\partial d_1}{\partial x} & \frac{\partial d_1}{\partial y} \\ \frac{\partial d_2}{\partial x} & \frac{\partial d_2}{\partial y} \\ \frac{\partial d_3}{\partial x} & \frac{\partial d_3}{\partial y} \\ \frac{\partial d_4}{\partial x} & \frac{\partial d_4}{\partial y} \end{bmatrix}$$

Since the $\mathbf{H}$ matrix is rectangular rather than square, and therefore uninvertible, a so-called pseudo-inversion matrix $(\mathbf{H}^{\mathrm{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathrm{T}}$ is used in (11) instead of $\mathbf{H}^{-1}$.

The described process is iteratively repeated until the Euclidean norm of $\Delta\hat{\mathbf{x}}$ falls below a predefined threshold [6,7,14].

The OLS algorithm is less accurate than the EKF, but it can be successfully used for coarse positioning. Furthermore, a position obtained in the OLS can be used to initialize the EKF. In the proposed system, the OLS is used also for this purpose.

Evaluation of the system

To evaluate the effectiveness of the implemented estimation algorithms, several tests of our system were conducted. The beacons were deployed around the area of interest and a user equipped with the mobile unit was moving along a predefined, marked route, which was a rectangle of the dimensions 6 x 4 meters.

The estimated tracks were compared with the real ones and the results obtained for the EKF and for the OLS are shown in Fig. 5 and Fig. 6, separately for both tested algorithms.

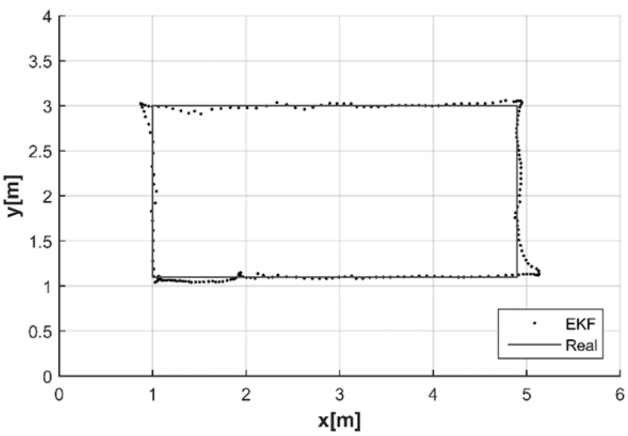

Fig.5. Positioning result obtained with EKF algorithm

As can be seen, in both cases the obtained positioning results closely follow the real travel path. The results from the EKF are very accurate during the straight fragments of the route, however, during rapid turns, the acquired path significantly deviates from the real one. These deviations, however, are quickly corrected. Although the maximum deviation in the presented test was 23.4 cm, the track obtained from the EKF usually differs from the real track by only a few centimeters or almost coincides with it entirely. The results from the OLS algorithm also resemble the real path, but there are bigger deviations during the motion of the user.

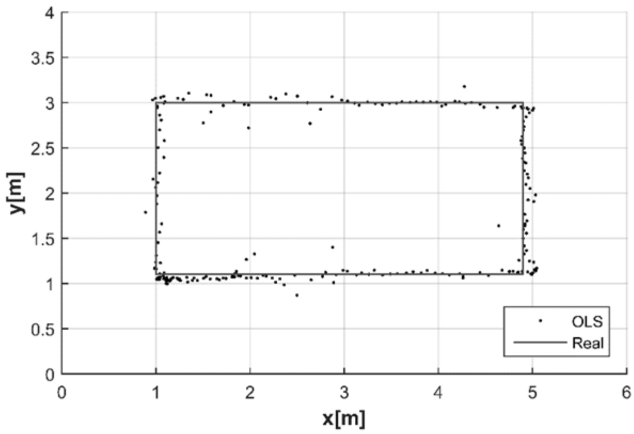

Fig.6. Positioning result obtained with OLS algorithm

Conclusion

Using ultrawideband modules in personal positioning systems allows to achieve very accurate distance measurements between beacons and a user which makes an accurate positioning inside buildings possible. The accuracy of the presented system is usually within a few centimeters which is more than enough in most personal navigation applications.

The designed system has a potential for further development. The four stationary beacons, which are used in the system, allow to navigate in three dimensions, therefore it would be relatively easy to implement 3D positioning algorithms.

Furthermore, the system's abilities can be extended by implementing more advanced positioning algorithms such as a modification of the Extended Kalman Filter which processes data sequentially and allows for positioning even when some distance measurements are not available.

Using inertial technology, e.g. a small and low-cost MEMS IMU, would bring additional benefits such as improvement of the accuracy and assurance that the position is determined continuously.

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