Algorithm for Pedestrian Navigation Combining IMU Measurements and Gait Models

P. Davidson and J. Takala

Tampere University of Technology, Finland

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Abstract—This paper presents a novel approach to INS velocity aiding in autonomous pedestrian navigation systems with body-mounted IMU. The proposed solution uses a kinetic model of human gait as a virtual velocity sensor. In this paper we show how an understanding of INS error dynamics and knowledge of human motion help to curb the divergence of INS computed horizontal velocity and tilt errors. Heading and heading gyro drift cannot be corrected with this method and require some additional procedures. This algorithm is based on Kalman filter and can be adapted for implementation on real-time pedestrian navigation systems equipped with 6 DOF IMU. The algorithm accuracy performance was investigated using data from indoor walking tests.

INTRODUCTION

High-performance autonomous pedestrian dead-reckoning (PDR) systems usually include 6 degrees-of-freedom (DOF) inertial measurement unit (IMU) to calculate position of the user. These systems don't rely on GPS signals and preinstalled infrastructure such as RF beacons, Wi-Fi routers, ultrasonic transmitters etc. Standard inertial navigation system (INS) calculates position by temporal integration of IMU data that comes from three accelerometers and three gyroscopes. Estimated position is calculated at regular time intervals. The unaided INS's position, velocity and attitude errors grow with time and can be quite significant especially when IMU consists of low-cost MEMS sensors. Therefore traditional unaided INS mechanization is impractical for pedestrian navigation.

One way to curb the divergence of errors in INS is to use external velocity and position aiding. In indoor scenarios without preinstalled infrastructure the options for external velocity and position aiding are very limited: building floor plans can be used for position update, Doppler radars for velocity update. But even these options are not always available.

An alternative navigation method takes advantage of biomechanics of walking. Recognizing that people move one step at a time, the pedestrian mechanization restricts error growth by propagating position estimates in a stride-wise fashion, rather than on a fixed time interval. Inertial sensors in a pedestrian dead reckoning (PDR) system are used to detect the occurrence of steps, and provide a means of estimating the distance and direction in which the step was taken. In this way position error is proportional to the number of steps or traveled distance. Many current PDR systems use foot mounted IMU which allows for zero-velocity update at every stride.

Our approach can be applied to PDR systems that include body-mounted IMU at waist or torso, which in some applications can be advantageous compared to foot-mounted sensors. In this paper we propose a novel approach for velocity update based on knowledge of human walking process. This approach gives us an alternative way to calculate traveled distance and velocity averaged during the step, which can be considered as a virtual measurement. The term "virtual" emphasizes the fact that there is no separate instrument for direct speed measurement. The speed is estimated using accelerometer measurements and additional information about pedestrian's movement, which is derived from the model of human gait kinematics.

The different characteristics of errors in INS output and in this virtual measurement make it possible to apply complementary filter methodology and significantly improve INS performance by keeping the horizontal velocity and tilt errors small. The processing of corrected IMU output results in accurate estimation of stride length and direction. This paper presents the real-world results from pedestrian indoor walking tests. The MEMS IMU with 10 deg/hr gyro bias stability was used in these tests. The reference position was estimated using the known waypoints in the building.

DYNAMICS OF HUMAN GAIT

Dynamics of human gait is a unique source of external velocity aiding for pedestrian navigation systems that has largely been overlooked by the engineers. Analysis of the human gait shows that the basic pattern
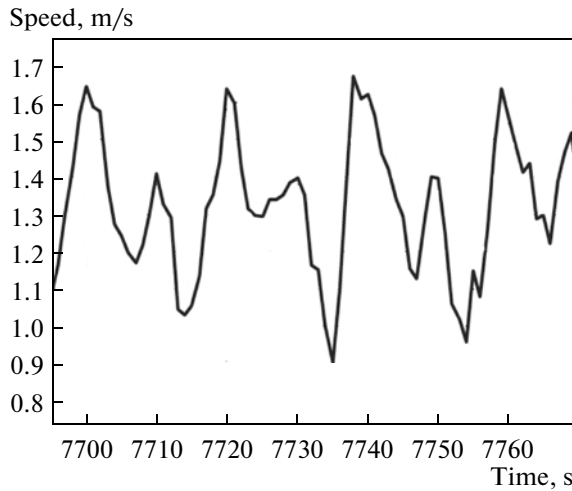
Speed, m/s

Fig. 1. Horizontal speed during walking.
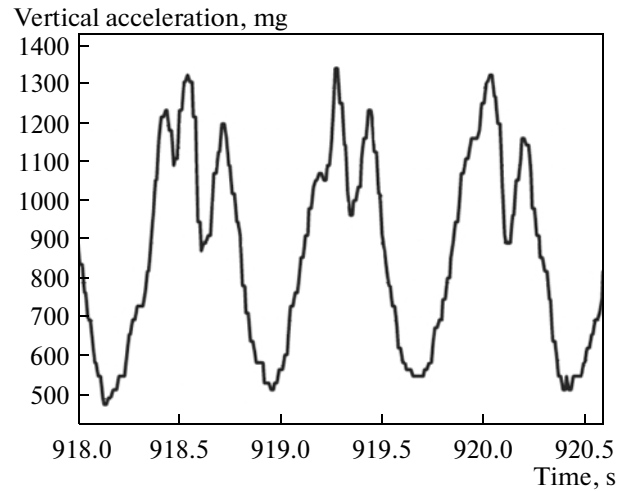
Vertical acceleration, mg

Fig. 2. Vertical acceleration during walking

of human motion during a walk is cyclical, repeatable and remarkably consistent between individuals [1]. At normal constant walking speed, the vertical and horizontal components of the body's centre of gravity velocity oscillate smoothly with the walking frequency equal to the step frequency. Examples of horizontal speed and vertical acceleration during normal walking are shown in Figs. 1 and 2.

The amplitude of vertical acceleration and vertical displacement are proportional to the step length. As a result, the stride events as well as stride length can be estimated using models of gait dynamics and measured motion parameters. When a foot hits the ground significant vertical acceleration is generated by the impact. Therefore the algorithms for stride occurrence detection can be based on the analysis of the acceleration pattern during walking. For example the body-mounted accelerometers can detect maximum or minimum of the vertical acceleration, which corresponds to the step occurrences. If the vertical acceleration exceeds the pre-defined threshold then the step occurrence is detected. Since the pattern of acceleration depends on type of movement (walking, running, going up or down stairs, etc.) and type of ground over which the person walks (hard, soft, slippery surface) the determination of threshold for reliable step detection is not so easy [3, 4].

Another way to process accelerometer data for step detection is to use zero-crossing of the acceleration magnitude signal. The zero-crossing method requires a tri-axial accelerometer to measure pedestrian movement. The magnitude of the acceleration vector can be computed by subtracting the local gravity from the measured magnitude of the acceleration vector. Footfall recognition is based on determination of the zero crossing of the acceleration magnitude signal. Since the norm of the acceleration vector is used the orientation of the sensor unit has no effect on the measure-

ment. Step detection is triggered when zero crossings fit in the recognition window [5].

Step length can be defined as the distance from the heel print of one foot to the heel print of the other foot. This is the distance traveled forward by a single leg. Stride length can mean the distance traveled by the heel of one foot to the next time that same foot strikes down — in other words, two steps, since in that time the other foot has also touched down once. During symmetric walking stride length is approximately twice the step size, therefore the terms stride length, step length and step size can be used interchangeably in most of the cases related to pedestrian navigation. The stride length depends on several factors such as walking velocity, step frequency and height of walker etc.

The algorithms for step length estimation generally fall into two groups: (1) algorithms based on biomechanical models and (2) algorithms based on empirical relationships. The example of the step length estimator based on biomechanical model is a kneeless biped, which is modeled as inverted pendulum with leg length l, and vertical displacement of the center of gravity h. In this case the estimation of step length is given by [11]

$$\Delta L_1 = K\sqrt{2lh - h^2} \qquad (1)$$

where K is a calibration constant. Empirical relation between the vertical acceleration and the step length is given by

$$\Delta L_2 = K\sqrt[4]{a_{max} - a_{min}} \qquad (2)$$

where a_{max}, a_{min} are the maximum and minimum values of the vertical acceleration during the step. These algorithms show good performance during normal walking on flat terrain. The step length estimation error is 2−5% of distance. The performance of these algorithms degrades rapidly when a person is walking, for example, on non-flat terrain or climbing on stairs.
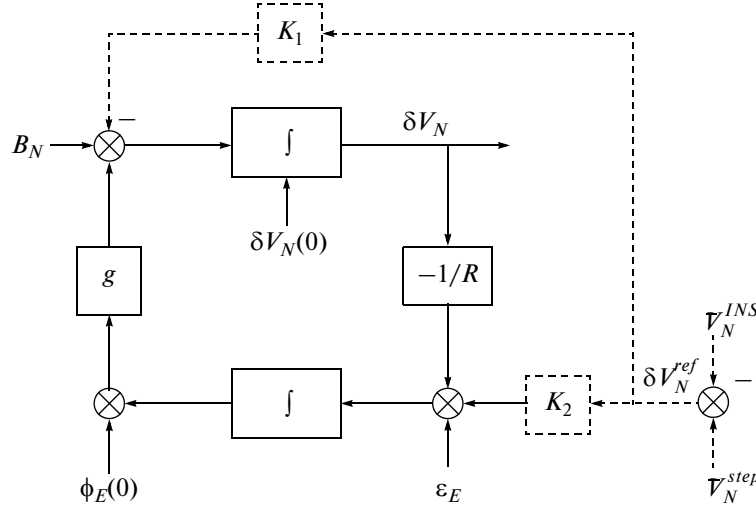
Fig. 3. Diagram of the INS's north channel error damping.

Average speed during the step can be calculated as the ratio between the step length and step duration. This ground speed can be also resolved into the north and the east velocity components using INS computed heading averaged over the same step. Thus the estimation of pedestrian velocity during the step is obtained. Since the velocity error of this kinetic model based estimator is a result of several independent error sources such as model error, measurement error, inaccuracy in step occurrence events it has a random distribution and can be approximated as Gaussian noise.

When the horizontal components of velocity are computed, the azimuth is taken from the INS. The azimuth error is a source of additional error in the north and the east velocity components. If the pedestrian's speed is 1 m/s and azimuth error is 1 degree the error in the horizontal velocity components will not exceed 0.015 m/s. In this case this error is smaller than the error in velocity estimated based on kinetic model of human gait. This error is also included in the velocity, which is estimated based on kinetic model of human gait.

FUSION OF IMU DATA AND PEDESTRIAN DYNAMICS

In our pedestrian navigation system the body mounted IMU contains three gyros and three accelerometers that measure the projections of absolute angular rate and specific force on their sensitivity axes. The navigation computations are performed in the local-level coordinate frame. The transformation matrix from the sensor frame to the local-level frame is calculated using output from gyroscopes. The mechanization equations are implemented as local-level terrestrial navigator without vertical channel. The description of the strapdown navigation algorithm can be found in [13, 14].

Position, velocity and attitude errors in a stand-alone INS grow with time. For short period of autonomous operation (1−1.5 hours) the propagation of horizontal velocity errors and tilts can be approximated by the Schuler oscillations. When the INS is assumed to be nominally level with altitude compensation and constant low speed, the single north channel error model is described by the following equations [8, 9]:

$$\delta \dot{V}_E = -g\varphi_N + B_E$$
$$\dot{\varphi}_N = \frac{\delta V_E}{R} + \varepsilon_N$$
$$\delta \dot{V}_N = g\varphi_E + B_N \qquad (3)$$
$$\dot{\varphi}_E = -\frac{\delta V_N}{R} + \varepsilon_E$$

where δV_E, δV_N are the north and east components of velocity error, φ_E, φ_N are the horizontal tilt errors, $B_E, B_N, \varepsilon_E, \varepsilon_N$ are the projections of accelerometer biases and gyro drifts on the local-level frame. The equations for the east channel are similar to (3). Note that under above assumptions the north, east and vertical channels are not coupled and can be processed separately. The block diagram representation of INS's north channel is shown in Fig. 3 by the solid lines [9].

A approach for oscillation damping, well known in control theory, is based on feedback loop to control the dynamic behavior of the system. A partially measured output is fed back to the controller where the difference between the reference and the output is amplified to change the input in desired way and obtain improved system performance. The damping of INS errors can be implemented using the external velocity information. The control inputs are shown in Fig. 3 by the dashed lines. The gains K_1 and K_2 can be pre-computed or calculated online.

In the case of pedestrian navigation, the kinetic model of gait is considered as a virtual sensor that can be used to estimate the step events and step size for a person while walking. As a result, the estimations of step size and step duration can be used to calculate average velocity over each step. The error in computed average velocity consists of the errors in step length model, inaccuracy in determining step duration and accelerometer measurement errors. The error components are not correlated with each other thus making the error in velocity random with little correlation in time. Since the error of this estimated average velocity is also not correlated with INS velocity error it can be used as an external velocity measurement for INS.

Even when a person is walking with almost constant speed, the velocity profile within each step reveals variations of about 0.3 m/sec around the average walking speed (fig. 1). Since the indicated INS velocity follows the same profile, the comparison of momentarily INS velocity with average velocity is not appropriate. Instead the indicated INS velocity averaged over one step can be compared with average velocity from an external measurement. As a result of this comparison, an estimation of the INS velocity error can be obtained.

Since the INS velocity error changes slowly it can be assumed constant during one step. In this case averaged over one step INS indicated velocity is calculated as the true average velocity plus the velocity error. The north component is given by

$$\bar{V}_N^{INS} = \frac{1}{(t_{k+1} - t_k)} \int_{t_k}^{t_{k+1}} \left(V_N^{true} + \delta V_N^{INS} \right) dt \tag{4}$$
$$= \bar{V}_N^{true} + \delta V_N^{INS}.$$

Where δV_N^{INS} is the north component of INS velocity error, $\bar{V}_N^{step}$ the average north velocity over one step calculated from the kinetic model, $\bar{V}_N^{INS}$ is the average north velocity calculated from the INS indicated velocity. Computations for the east component of the INS velocity error are similar to that of the north component. The measurement of the INS velocity error can be obtained by taking the difference between INS velocity, averaged over one step and the kinetic model computed velocity.

$$z = \begin{bmatrix} \bar{V}_N^{INS} - \bar{V}_N^{step} \\ \bar{V}_E^{INS} - \bar{V}_E^{step} \end{bmatrix} = \begin{array}{c} \delta V_N^{INS} + w_N \\ \delta V_E^{INS} + w_E \end{array}. \tag{5}$$

Here w_N, w_E are the velocity errors of the kinetic model based velocity estimator. While compuing the INS velocity error using (5) it was also assumed that the velocity estimated based on the kinetic model has a random error, which is assumed to be distributed as a random Gaussian noise with velocity variance of 0.0025 m²/sec². This virtual measurement of INS velocity error can be performed at every step.

Let us formulate the mathematical system model for horizontal velocities and tilts in terms of error state space. Only the north channel equations are described since the data processing for the east channel is similar. Since in pedestrian navigation systems the accelerometer bias has smaller effect than the other error sources there will be three variables of primary interest for each channel: error in INS indicated velocity, tilt error, and gyro drift rate. In terms of these variables, the state differential equations for the north channels become:

$$\begin{bmatrix} \delta \dot{V}_N \\ \dot{\phi}_E \\ \dot{\varepsilon}_E \end{bmatrix} = \begin{bmatrix} 0 & g & 0 \\ -1/R & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta V_N \\ \phi_E \\ \varepsilon_E \end{bmatrix} + \begin{bmatrix} n_a \\ 0 \\ n_g \end{bmatrix} \tag{6}$$

where n_a, n_g is the noise. The measurement to be used as the input to the Kalman filter is the difference between average velocities given by Eqs. 5. In terms of the error state notation it becomes

$$z(t_k) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta V_N(t_k) \\ \phi_E(t_k) \\ \varepsilon_E(t_k) \end{bmatrix} + w(t_k). \tag{7}$$

Based upon system and measurement models the Kalman filter can be specified. First consider propagation from sample time t_{k-1} to time t_k. It is assumed that when the measurement is obtained the update computations are performed and the corrective signal applied to the INS. The optimal error estimate at time t_{k-1} is

$$\hat{x}(t_{k-1}) = \begin{bmatrix} \delta \hat{V}_N(t_{k-1}) \\ \hat{\phi}_E(t_{k-1}) \\ \hat{\varepsilon}_E(t_{k-1}) \end{bmatrix}. \tag{8}$$

This estimate serves as the corrective signal to the INS, which is applied at time t_{k-1}. Thus the predicted state at time t_k before the new measurement is obtained is

$$\hat{x}(t_k^-) = \begin{bmatrix} \delta \hat{V}_N(t_k^-) \\ \hat{\phi}_E(t_k^-) \\ \hat{\varepsilon}_E(t_k^-) \end{bmatrix} = 0. \tag{9}$$

So there is no need to compute the predicted state explicitly. The covariance propagation equation is

$$P(t_k^-) = \Phi(t_k, t_{k-1}) P(t_{k-1}^+) \Phi^T(t_k, t_{k-1}) + Q(t_k) \tag{10}$$

where $\Phi(t_k, t_{k-1})$ is the state transition matrix. To update the estimate at the time when new measurement is obtained the filter gain is calculated

$$K(t_k) = P(t_k^-) H^T \left(H P(t_k^-) H^T + R \right)^{-1}. \tag{11}$$

The covariance update is

$$P(t_k^+) = P(t_k^-) - K(t_k) H P(t_k^-). \tag{12}$$

Since $\hat{x}(t_k^-)$ is zero the optimal state estimate update becomes

Fig. 4. The assembly of 6 DOF IMU, batteries and readout electronics.

Fig. 5. Location of the IMU on the body during the test.

Location of the IMU on the body during the test

$$\hat{x}\left(t_k^+\right) = K\left(t_k\right) z\left(t_k\right) \qquad (13)$$

The last formula represents the control inputs that are fed back into INS to reduce the horizontal velocity and tilt errors. Horizontal gyro drift can be also corrected in similar way. But this correction was not implemented in the current version of our algorithm.

EXPERIMENTAL RESULTS

The proposed method for INS velocity aiding was tested with actual data from the indoor walking tests. The 170 meter test route inside the typical office building is shown in Fig. 6. The true pedestrian path is shown by solid line 1. The test scenario included different types of movement: walking with variable step length and frequency, going up or down stairs, standing, making sharp turns and opening the doors. The total time of the test was about 5 minutes. The pedestrian dead-reckoning system included 6 DOF IMUs composed of three VTI Technologies SCC1300-D02 combined gyroscopes and accelerometers with digital SPI interfaces [12]. This is a self-contained device for inertial data collection. In addition to three gyros and accelerometers it includes also the batteries, memory card and all necessary electronics for data collection. The complete unit is shown in Fig. 4.

The INS computed path is shown in Fig. 6 by the asterisks. Our method can reduce only the distance error in PDR systems. Along-track (distance) error during this test does not exceed 2% of travelled distance. The results can be improved when horizontal gyros' drifts are compensated. But the largest error is
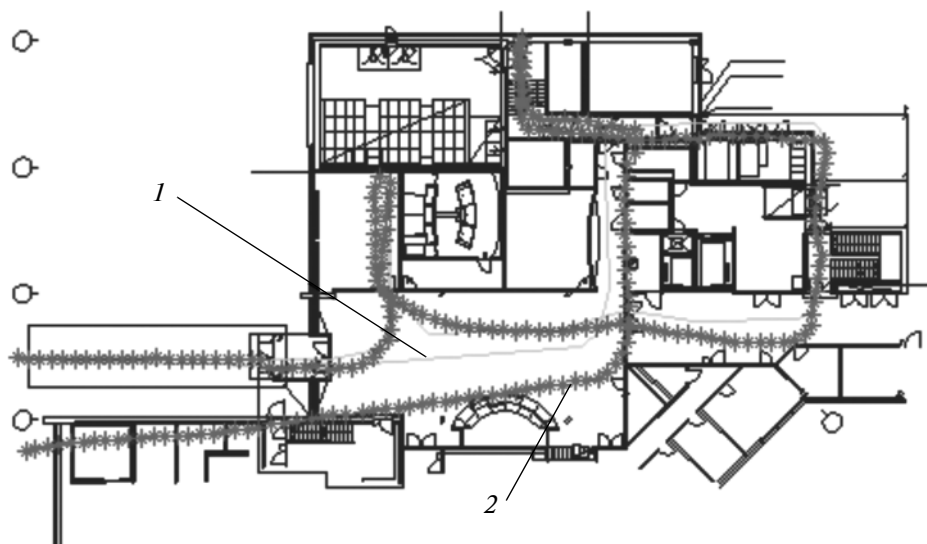
Fig. 6. The walking path inside the building: The true path is shown by solid line *1*.
The INS computed path *2* is shown by the asterisks.

caused by heading error. Heading cannot be corrected with this algorithm and other methods, for example, map-matching can be used to reduce the heading error.

CONCLUSIONS

We proposed a novel approach for INS external velocity aiding in pedestrian navigation systems. Our approach can be applied to body-mounted INS, which in some applications can be advantageous compared to foot-mounted sensors mainly because the body mounted IMU is isolated from shocks and high dynamics. For the same MEMS gyros the measurement error can be significantly higher if the gyros are exposed to shocks. Therefore the PDR systems with body mounted IMU have better performance in heading estimation. In addition to this the body mounted IMU is preferable for the motion classification.

The method uses kinetic model of human gait which gives us an alternative way to calculate traveled distance and velocity averaged during the step which can be considered as a virtual velocity measurement. The different characteristics of errors in INS output and in this virtual measurement make it possible to apply complementary filter methodology and significantly improve INS performance by keeping the horizontal velocity and tilt errors small. The distance error is about 2% of traveled distance. Our approach does not have restrictions on pedestrian movement. However reliable velocity update is possible only during normal walking or standing.

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