Robust velocity estimation for legged robot using on-board sensors data fusion

Paweł Wawrzyński
Institute of Control
and Computation Engineering
Warsaw University of Technology
Warszawa 00-665, ul. Nowowiejska 15/19
Email: p.wawrzynski@elka.pw.edu.pl

Jakub Możaryn
and Jan Klimaszewski
Institute of Automatic
Control and Robotics
Warsaw University of Technology
Warszawa 02-525, ul. Św. Boboli 8
Email: j.mozaryn@mchtr.pw.edu.pl,
j.klimaszewski@mchtr.pw.edu.pl

***Abstract*—Availability of momentary velocity of a legged robot is essential for its efficient control. However, estimation of the velocity is difficult, because the robot does not need to touch the ground all the time or its feet may twist. In this paper we introduce a method for velocity estimation in a legged robot that combines kinematic model of the supporting leg, readouts from an inertial sensor, and Kalman filter. The method alleviates all the above mentioned difficulties.**

***Index Terms*—legged locomotion, velocity estimation, Kalman filter.**

I. Introduction

Knowledge of the robot state i.e., global position, velocity, and acceleration, is crucial to acquire good performance for most legged locomotion and posture controllers. While it is possible to directly measure acceleration and position, precise velocity estimation is usually a difficult task [1] [2]. The most popular sensors used for mobile robot position measurement include digital encoders, cameras [3] [4], and GPS navigation devices [5] [6]. However, GPS measurements have low accuracy and can be used only outdoors, while vision based methods require massive computations for large image analysis.

Velocity estimation is possible with the use integration of readouts from Inertial Measurement Units (IMUs). These devices may be sufficiently accurate but then, they are large, heavy, and expensive. On the other hand, small and inexpensive IMUs lack sufficient accuracy [2].

Recent availability of low-cost IMUs made it possible to use them in popular legged robots. Many researchers show that joints position, feet contact, robot kinematic model, and IMU measurements data can be successfully used for legged robot pose estimation. Lin et al. [7] introduced full body pose estimation system for hexapod robot. The authors show that traditional leg kinematics model, joint position, and feet contact sensors can be replaced by strain gauge based empirical leg configuration model. In [2] that method was broadened by adding IMU measurements, and extended Kalman filter (EKF). Chilian et al. [4] show that it is possible to estimate legged robots state combining drift-affected IMU measurements with additional drift-free sensors. This includes measurements of joints positions and torques aided with a system based on stereovision. Reinstein et al. [8] proposed an alternative method to reduce IMU bias and, moreover, addressed foot slippage problem by using period-based measurement data indicators analysis. Finally, Bloesh et al. [9] presented framework for full body pose estimation, that can be viewed as a simultaneous localization and mapping (SLAM) algorithm.

In this paper we propose a method for legged robot velocity estimation based on robot kinematics model, measurement data from IMU, digital encoders in servomotors, feet contact sensors, and EKF. In contrary to other approaches, the proposed method can be used in any terrain, it is robust to foot twist, and it allows for limited foot slippage. In the experimental study, this method is applied to customized Bioloid biped robot.

The structure of this paper is as follows: Section II introduces an overview of the sensory suite, the experimental setup, and presents the formal problem description. Section III describes the notation used. The proposed solution is presented in Section IV, where basic tools are discussed, and Section V, where EKF is used for the sensor fusion. Section VI presents an experiments with the proposed approach. Finally in section VII brief discussion of the obtained results is given.

II. Problem formulation

At first the experimental framework is presented to make the general problem formulation and the proposed method description more intuitive.

A. Experimental framework

Fig. 1 presents the customized Bioloid robot. A body of Bioloid[1] is composed of identical 18 servomotors: 6 in each leg and 3 in each arm. The robot is 35 cm tall and weighs about 2 kg. An additional box attached to the robot back[2] contains a small PC with Linux on board as well as IMU[3].

[1] Bioloids are serially manufactured by Robotis: `www.robotis.com`.

[2] BioloBrainS1. It is serially manufactured by Altronit: `www.altronit.com`.

[3] ADIS 16365. It is an accelerometer and gyroscope in a single chip manufactured by Analog Devices: `www.analog.com`.

978-1-4673-5508-7/13/$31.00 ©2013 IEEE

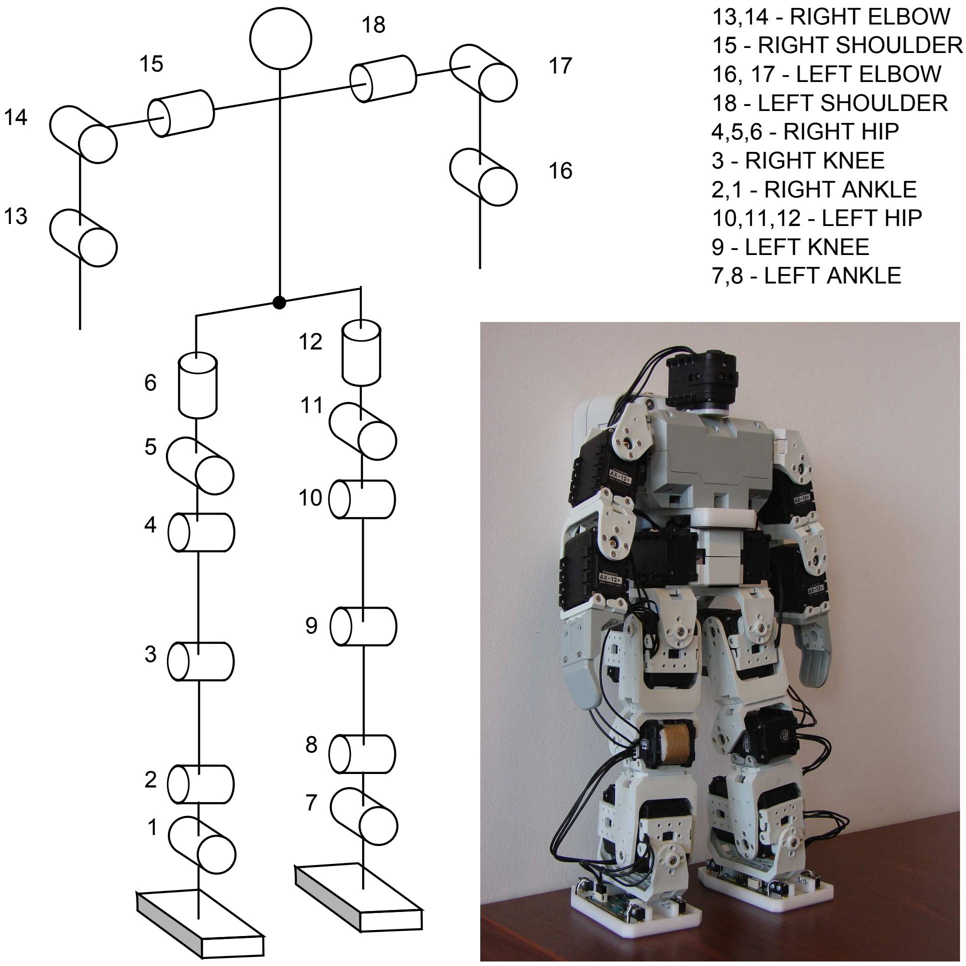

Fig. 1. Customized Bioloid used in the experiments.

Each foot is equipped with 4 touch sensors each.[4]

The problem is to estimate robot momentary velocity and tilt, while it is walking.

B. Generic problem formulation

The general problem is formulated as follows: There is given a legged robot with IMU attached to it. Joints of the robot are equipped with position encoders, and its feet are equipped with contact sensors. The problem is to estimate momentary velocity of the robot and acceleration due to gravity in the coordinate system that is immobile in relation to the ground and its orientation is parallel to the momentary orientation of IMU. It is understood that having these information, it is possible to express robot velocity in any coordinate system of interest.

III. Notation

Different coordinate systems (i.e., frames) will be distinguished as follows:

- An *immobile* frame is understood as the coordinate frame not moving in relation to the ground.
- A *frame of the sensor/link* is understood as the coordinate frame attached to the sensor/link.
- An *immobile frame of the sensor/link* is understood as the immobile frame that is at the moment parallel to frame of the sensor/link.

For a description of robot kinematics, the coordinate frames for each joint, were chosen according to methodology described in [10]. We use *Denavit-Hartenberg* (DH) [11] convention and the "right hand rule" for selecting coordinate frames. Therefore, there are used four parameters associated with link i and joint i.

- **joint angle** θ_i, is the angle from the x_{i-1} axis to the x_i axis about the z_{i-1} axis,
- **link length** a_i, is the distance form the intersection of the z_{i-1} axis with the x_i axis to the origin of the i-th frame along the x_i axis (or the shortest distance between the z_{i-1} and z_i axes),
- **link offset** d_i, is the distance from the origin of the $(i-1)$ coordinate frame to the intersection of the z_{i-1} axis with the x_i axis along the z_{i-1} axis
- **link twist** α_i, is the offset angle from the z_{i-1} axis to the z_i axis about x_i axis.

[4]BioloFeet. They are also manufactured by Altronit.

TABLE I
DH PARAMETERS OF THE RIGHT LEG OF BIOLOID ROBOT

joint	α_{i-1}	a_{i-1}	d_i	θ_i
1	$-\frac{\pi}{2}$	0	0	θ_1
2	0	a_1	0	θ_2
3	0	a_2	0	θ_3
4	$\frac{\pi}{2}$	0	0	θ_4
5	$\frac{\pi}{2}$	0	d_5	θ_5
6	0	0	0	θ_6

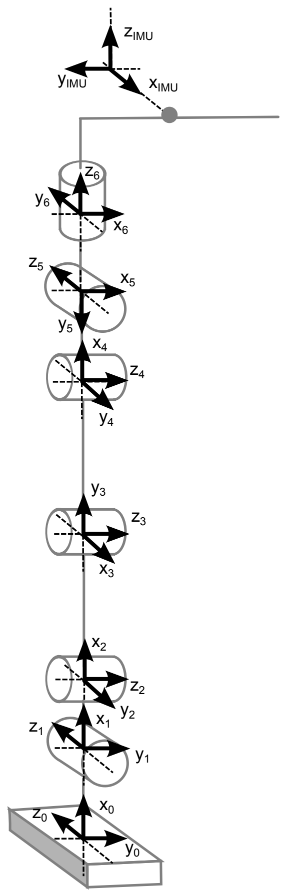

Fig. 2. Coordinate frames of the right leg of Bioloid robot

It is assumed that a leg of the robot is a kinematic chain with rotational joints. The joints are indexed by $i = 1, \ldots, n$, where i-th joint is between links i-the and $i+1$-st. Link 1-st is the foot, and link $n+1$-st is between n-th joint and the inertial sensor. The coordinate frames, associated with links in the right Bioloid robot leg, are presented in Fig. 2, with D-H parameters gathered in Table I.

Orientation of the inertial sensor is defined by the unit vectors w^x, w^y, w^z of its frame axes expressed in the coordinates of the last link. The following notation will be applied below.

- $p_i \in R^{3\times1}$ is a position of IMU in the frame of i-th link,
- $q \in R^{3\times1}$ is an acceleration vector measured by IMU, i.e., a sum of linear acceleration and acceleration due to gravity,
- $\omega \in R^{3\times1}$ is angular velocity of IMU in its immobile frame,
- $g \in R^{3\times1}$ is the gravity vector in IMU frame,
- $v \in R^{3\times1}$ is the velocity vector of IMU in its immobile frame,
- δ is constant time elapsing between consecutive IMU measurements.
- $R_i(\theta_i) \in R^{3\times3}$ is a rotation matrix between $i+1$-st frame and i-th frame; it is defined by D-H parameters [10],
- $f(\beta, x) \in R^{3\times1}$ is a vector that is a result of simultaneous rotations of vector x about each axis of the frame by the angles contained in vector $\beta \in R^{3\times1}$. (Usually f is denoted as a product of appropriate rotation matrix and x, but here it would make the discussion more complex.)
- $\widehat{x}$ is an estimate (or measurement) of the true value x, e.g., $\widehat{q}$ is the accelerometer readout, and $\widehat{\omega}$ is the gyroscope readout,
- $\widetilde{x} = \widehat{x} - x$ is an error of this estimate (or measurement),
- x_i vs. x vs. x_{n+1}: if x_i denotes a certain vector in the frame of i-th joint, x denotes the same value in the immobile frame of IMU, and x_{n+1} denotes the same value in the frame of IMU that is moving with IMU. (There are n joints, hence $n+1$-st frame is the frame of IMU).

IV. BASIC TOOLS

A. Velocity estimation with inertial sensor only

Suppose that there is one initial moment when the robot is immobile. Then, the accelerometer measures acceleration due to gravity, and velocity is zero, i.e.,

$$\widehat{g} = \widehat{q}, \quad \widehat{v} = 0. \tag{1}$$

Afterwards, when the robot is moving, both the velocity and gravity (in the immobile frame of IMU) rotates with angular velocity opposite to one measured by the gyroscope, and the velocity increments by acceleration measured by the accelerometer. It is assumed for simplicity that in the time interval of δ, both angular velocity and acceleration are constant. Then, the gravity and velocity change in this interval as

$$\widehat{g} \leftarrow f(-\widehat{\omega}\delta/2, \widehat{g}), \tag{2}$$
$$\widehat{v} \leftarrow f(-\widehat{\omega}\delta, \widehat{v}) + (\widehat{q} - \widehat{g})\delta, \tag{3}$$
$$\widehat{g} \leftarrow f(-\widehat{\omega}\delta/2, \widehat{g}). \tag{4}$$

In (2–4) the gravity is rotated twice to calculate its middle value that is applied to eliminate gravity from acceleration measurement.

B. Velocity estimation with kinematics only

In order to compute velocity of the inertial sensor in its frame, we proceed as follows:

1) Velocity of the inertial sensor is computed in the frame of each joint in the leg kinematic chain, from IMU to the foot. In order to compute the velocity, location of

IMU, described in each frame down the leg is computed additionally. In the frame of $n+1$-st link to which IMU is attached, the sensor is immobile, therefore

$$p_{n+1} = 0, \tag{5}$$
$$\widehat{v}_{n+1}^{K} = 0. \tag{6}$$

where $\widehat{v}_i^K$ is the velocity estimation from kinematics of Bioloid in i-th coordinate frame. Then, for $i = n, \dots, 1$ (i.e. down the leg) IMU position is translated from one frame to another. The sensor velocity is rotated from one frame to another and incremented according to angular velocity of i-th joint as follows

$$p_i = R_i(\theta_i)[l_i + p_{i+1}], \tag{7}$$
$$\widehat{v}_i^K = R_i(\theta_i)\widehat{v}_{i+1}^K + p_i \times z_i\dot{\theta}_i. \tag{8}$$

2) Unit vectors of IMU frame axes are expressed in the frame of each joint in the leg kinematic chain, from the sensor to the foot. In the frame of the last link, the unit vectors of IMU frame axes are known:

$$w_{n+1}^x = w^x, w_{n+1}^y = w^y, w_{n+1}^z = w^z.$$

Then, down the leg, these vectors are rotated according to the position of the consecutive servomotor, namely

$$w_i^{x/y/z} = R_i(\theta_i)w_{i+1}^{x/y/z}. \tag{9}$$

3) Finally, the velocity of the inertial sensor, computed in the foot frame, $\widehat{v}_1^K$, is projected on unit vectors of IMU frame. That is, the velocity estimate, $\widehat{v}^K$, of IMU in its own immobile frame, $\widehat{v}^K$, is computed as

$$\widehat{v}^K = [\widehat{v}_1^K w_1^x, \widehat{v}_1^K w_1^y, \widehat{v}_1^K w_1^z]^T. \tag{10}$$

C. Velocity estimation with kinematics and gyroscope

Velocity computation of the inertial sensor only by means of the kinematic model of the leg, requires assumption that the foot is immobile. However, this assumption is now withdrawn. Namely, on the basis of the gyroscope readout, rotation of each link, from the last one to the foot will be computed. Then, having position of the inertial sensor in the foot frame and angular velocities of the foot, velocity of the inertial sensor in its immobile frame can be computed. The gyroscope measures the angular velocity vector coefficients in its own immobile frame. This vector has to be translated into angular velocities in the immobile frame of the last link, that is

$$\widehat{\omega}_{n+1} = w^x\widehat{\omega}^x + w^y\widehat{\omega}^y + w^z\widehat{\omega}^z. \tag{11}$$

Then, for $i = n, \dots, 1$, angular velocity of i-th link is computed as a transformed angular velocity of $i+1$-st link updated by the rotation of i-th joint:

$$\widehat{\omega}_i = R_i(\theta_i)\widehat{\omega}_{i+1} - w_i^z\dot{\theta}_i. \tag{12}$$

Having rotation of the foot in its own immobile frame, $\widehat{\omega}_1$, position of IMU in the foot frame, p_1, and velocity of the sensor in the foot frame, $\widehat{v}_1^K$, velocity of the sensor in the immobile frame parallel at the moment to the foot frame can be computed, namely

$$\widehat{v}_1^{KG} = \widehat{v}_1^K + \widehat{\omega}_1 \times p_1. \tag{13}$$

where $\widehat{v}_1^{KG}$ is the velocity estimate based on the gyroscope measurement and kinematics of the robot.

Then, velocity estimate of IMU in its own, immobile frame, can be expressed as follows

$$\widehat{v}^{KG} = [\widehat{v}_1^{KG}w_1^x, \widehat{v}_1^{KG}w_1^y, \widehat{v}_1^{KG}w_1^z]^T. \tag{14}$$

V. SOLUTION

In this section tools from the previous section, and Extended Kalman Filter are combined to estimate the state of the robot inertial sensor. In order to apply Extended Kalman Filter we need to define three entities: (i) state, (ii) the model of dynamics, (iii) the model of observation.

A. State of inertial sensor

State of the sensor encompass the vector of acceleration due to gravity, expressed in the sensor immobile frame, g, and linear velocity of the sensor in relation to the ground, expressed in the same frame, v:

$$\text{state} = \begin{bmatrix} g \\ v \end{bmatrix}. \tag{15}$$

B. Model of dynamics

Defining evolution of the state we consider $\widehat{\omega}$ and $\widehat{q}$ as inputs to the dynamical system. $\widehat{\omega}$ is assumed to be the sum of true angular velocity and zero-mean noise, $\widetilde{\omega}$. Similarly, $\widehat{q}$ is assumed to be the sum of true acceleration and zero-mean noise, $\widetilde{q}$. Then, for infinitesimal δ state of the sensor evolves as

$$g \leftarrow f(-(\widehat{\omega} - \widetilde{\omega})\delta/2, g), \tag{16}$$
$$v \leftarrow f(-(\widehat{\omega} - \widetilde{\omega})\delta, v) + (\widehat{q} - \widetilde{q} - g)\delta, \tag{17}$$
$$g \leftarrow f(-(\widehat{\omega} - \widetilde{\omega})\delta/2, g). \tag{18}$$

After linearisation around $(\widehat{\omega} - \widetilde{\omega})\delta = 0$, the above assignments have the following forms

$$g \leftarrow g - \frac{\partial f(\beta, g)}{\partial(\beta = 0)}\widehat{\omega}\delta + \frac{\partial f(\beta, g)}{\partial(\beta = 0)}\widetilde{\omega}\delta \tag{19}$$
$$v \leftarrow v - \frac{\partial f(\beta, v)}{\partial(\beta = 0)}\widehat{\omega}\delta + \frac{\partial f(\beta, v)}{\partial(\beta = 0)}\widetilde{\omega}\delta + \widehat{q}\delta - \widetilde{q}\delta - g\delta \tag{20}$$
$$+ \frac{\partial f(\beta, g)}{\partial(\beta = 0)}\widehat{\omega}\delta^2/2 - \frac{\partial f(\beta, g)}{\partial(\beta = 0)}\widetilde{\omega}\delta^2/2. \tag{21}$$

Let each component of $\widetilde{\omega}$ and $\widetilde{q}$ are stochastically independent and have standard deviations, respectively

$$\sigma_\omega > 0, \quad \sigma_q > 0 \tag{22}$$

Then, the above assignments may be written in the following matrix form

$$\begin{bmatrix} g \\ v \end{bmatrix} \leftarrow F\begin{bmatrix} g \\ v \end{bmatrix} - C\begin{bmatrix} \widehat{\omega}/\sigma_\omega \\ \widehat{q}/\sigma_q \end{bmatrix} + C\begin{bmatrix} \widetilde{\omega}/\sigma_\omega \\ \widetilde{q}/\sigma_q \end{bmatrix} \tag{23}$$

where

$$F = \begin{bmatrix} I & 0 \\ -I\delta & I \end{bmatrix} \tag{24}$$

$$C = \begin{bmatrix} \frac{\partial f(\beta,g)}{\partial(\beta=0)}\delta\sigma_\omega & 0 \\ \frac{\partial f(\beta,v)}{\partial(\beta=0)}\delta\sigma_\omega - \frac{\partial f(\beta,g)}{\partial(\beta=0)}\delta^2\sigma_\omega/2 & -I\delta\sigma_q \end{bmatrix} \tag{25}$$

and

$$\frac{\partial f(0,x)}{\partial(\beta=0)} = \begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix}. \tag{26}$$

C. Model of observation

The observation model is the simplest possible, namely,

$$\widehat{v}^{KG} = v + \widetilde{v}^{KG}$$

where $\widetilde{v}^{KG}$ is the error of velocity estimation with the use of kinematics and gyroscope. Let

$$\sigma_v > 0 \tag{27}$$

denote standard deviation of linear velocity estimation error.

D. Integration

Application of Extended Kalman Filter to estimation of the state of the inertial sensor leads to the following equations:

Prediction:

State estimate update:

$$\widehat{g} \leftarrow f(-\widehat{\omega}\delta/2, \widehat{g}), \tag{28}$$

$$\widehat{v} \leftarrow f(-\widehat{\omega}\delta, \widehat{v}) + (\widehat{q} - \widehat{g})\delta, \tag{29}$$

$$\widehat{g} \leftarrow f(-\widehat{\omega}\delta/2, \widehat{g}). \tag{30}$$

State estimate covariance matrix update:

$$P \leftarrow FPF^T + CC^T. \tag{31}$$

Correction:

Correction only takes place when it is possible to estimate the velocity with the use of kinematics and gyroscope.

Velocity error:

$$\widetilde{v} = \widehat{v}^{KG} - \widehat{v} \tag{32}$$

Auxiliary matrices; 0 and I below are appropriate 3×3 matrices:

$$H = [0\ I] \tag{33}$$

$$S = HPH^T + I\sigma_v^2. \tag{34}$$

Kalman gain:

$$K = PH^T S^{-1}. \tag{35}$$

Correction:

$$\begin{bmatrix} \widehat{g} \\ \widehat{v} \end{bmatrix} \leftarrow \begin{bmatrix} \widehat{g} \\ \widehat{v} \end{bmatrix} + K\widetilde{v}. \tag{36}$$

State estimate covariance matrix update:

$$P \leftarrow (I - KH)P. \tag{37}$$

VI. Experimental study

To verify the methodology described in Chapter IV and V, the experiment was carried using the customized Bioloid robot, described in Chapter II. The robot was supposed to walk along the straight line. Robot control system was based on reinforcement learning framework developed in [12]. During the experiment velocity vector in immobile IMU frame was periodically estimated. IMU readouts are available every 10ms which determines frequency of Kalman predictions. The kinematic model is applied to estimate velocity every 33ms which determines frequency of Kalman corrections.

In Fig. 3 the time series of velocity estimates along x axis are presented. Four estimates are computed simultaneously: one based on IMU only (Sec. IV-A), one based on the kinematic model (Sec. IV-B), one based on the kinematic model and gyroscope readouts (Sec. IV-C), and one based on Kalman filtering (Sec. V). The graphs lead to the following conclusions:

- Readout errors accumulate in the estimate based on IMU only. Therefore, this estimate becomes useless in several seconds.
- Velocity estimate based on the kinematic model are very noisy because of limited accuracy of servo encoders.
- Combining gyroscope readouts with the kinematic model in order to eliminate foot twisting introduces significant difference to velocity estimates.
- Noise in the estimate that results from filtering is significantly reduced.

The estimated average velocity along the immobile IMU x axis was calculated as

$$\widehat{v}_{\text{av}x} = \sum_{k=1}^{N} \widehat{v}_x(k) \tag{38}$$

Where k is the sample number, N is the number of samples. The experiment lasted for about 28 seconds and estimated average velocity was $\widehat{v}_{\text{av}x} = 3,28$ cm/s. During that time the robot walked about one meter and real average velocity was equal to $v_{\text{av}x} = 3.57$ cm/s. Therefore there was about 8% of difference between estimated and real value of average velocity along the immobile IMU x axis.

VII. Conclusions

In this paper a method was proposed for biped robot velocity estimation based on leg kinematics model, and measurement data from low-cost Inertial Measurement Unit (IMU). Extended Kalman Filter was used for the sensor data fusion. In the experimental study, this method was applied to customized Bioloid biped robot moving along the straight line.

The proposed method can be used in any terrain because it does not make any assumptions regarding orientation of the foot while it touches the ground. The measurements from gyroscope are transformed to estimate foot twist and utilized for more accurate velocity estimation, which is a significant advantage of this approach. Moreover, the method is immune to limited foot slippage, because the use of EKF makes the

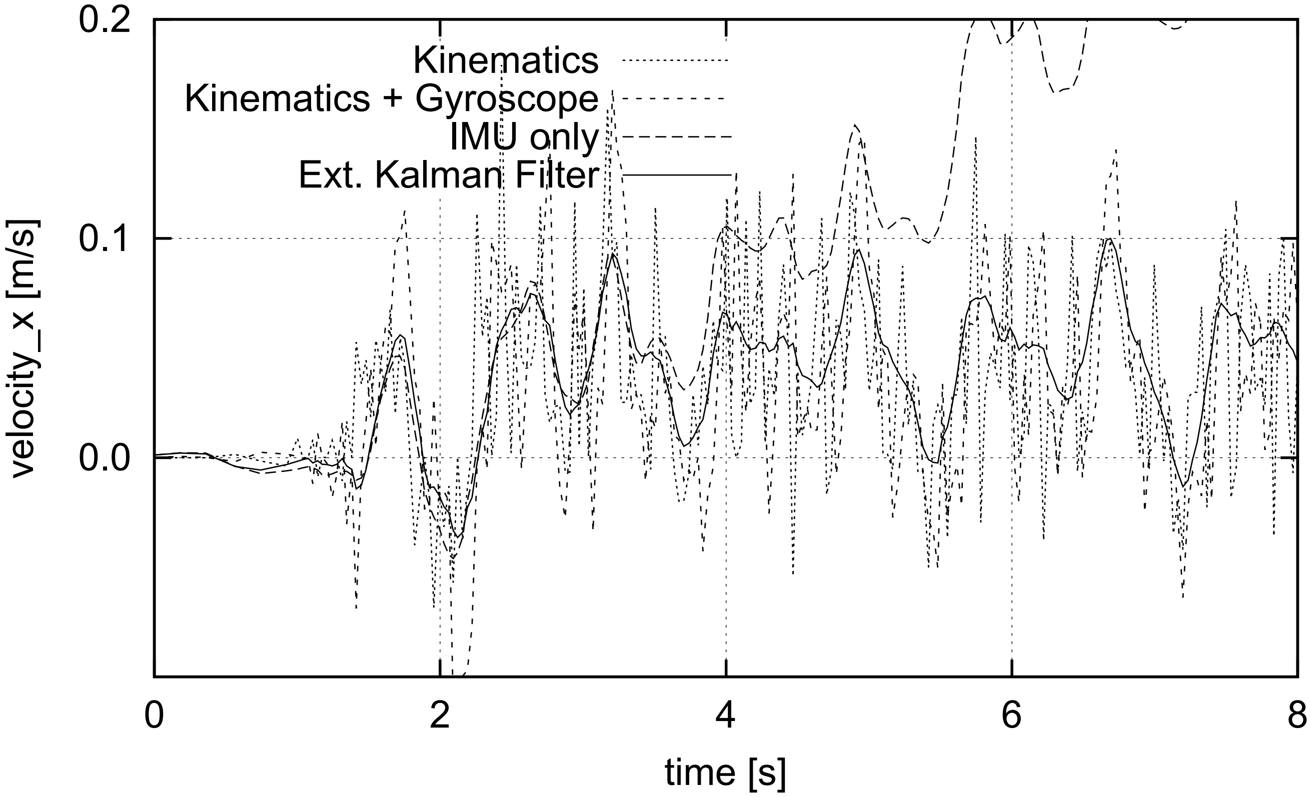

Fig. 3. Estimated velocity coefficient along axis x of the immobile IMU frame.

kinematic model of the leg only a low frequency attractor for the velocity estimate.

REFERENCES

[1] P. Belanger, P. Dobrovolny, A. Helmy, and X. Zhang, "Estimation of angular velocity and acceleration from shaft-encoder measurements," *The Internattional Journal of Robotics Research*, vol. 17, no. 11, pp. 1225–1233, 1998.

[2] P.-C. Lin, H. Komsuoglu, and D. Koditschek, "Sensor data fusion for body state estimation in a hexapod robot with dynamical gaits," *Robotics, IEEE Transactions on*, vol. 22, no. 5, pp. 932–943, 2006.

[3] D. van der Lijn, G. A. D. Lopes, and R. Babuska, "Motion estimation based on predator/prey vision," in *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, 2010, pp. 3435–3440.

[4] A. Chilian, H. Hirschmuller, and M. Gorner, "Multisensor data fusion for robust pose estimation of a six-legged walking robot," in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, 2011, pp. 2497–2504.

[5] J. Cobano, J. Estremera, and P. G. de Santos, "Location of legged robots in outdoor environments," *Robotics and Autonomous Systems*, vol. 56, no. 9, pp. 751 – 761, 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921889007001881

[6] B. Gassmann, F. Zacharias, J. Zollner, and R. Dillmann, "Localization of walking robots," in *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, 2005, pp. 1471–1476.

[7] P.-C. Lin, H. Komsuoglu, and D. Koditschek, "A leg configuration measurement system for full-body pose estimates in a hexapod robot," *Robotics, IEEE Transactions on*, vol. 21, no. 3, pp. 411–422, 2005.

[8] M. Reinstein and M. Hoffmann, "Dead reckoning in a dynamic quadruped robot: Inertial navigation system aided by a legged odometer," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, 2011, pp. 617–624.

[9] M. Bloesch, M. Hutter, M. Hoepflinger, S. Leutenegger, C. Gehring, C. D. Remy, and R. Siegwart, "State estimation for legged robots - consistent fusion of leg kinematics and IMU," in *Proceedings of Robotics: Science and Systems*, Sydney, Australia, July 2012.

[10] K. S. Fu, R. C. Gonzalez, and C. S. G. Lee, *Robotics: Control, Sensing, Vision, and Inteligence*. McGraw-Hill Book Company, 1987.

[11] J. Denavit and R. S. Hartenberg, "A kinematic notation for lower-pair mechanisms based on matrices," *Journal of Applied Mechanics*, vol. 23, pp. 215–221, 1955.

[12] P. Wawrzynski, "Autonomous reinforcement learning with experience replay for humanoid gait optimization," in *Proceedings of the International Neural Network Society Winter Conference (INNS-WC2012), Procmedia*, 2012, pp. 205–211.