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Novel approach to human walking speed enhancement based on drift estimation

Krzysztof Brzostowski*

Wroclaw University of Science and Technology, Wyb. Wyspianskiego 27, 50-370 Wroclaw, Poland

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ABSTRACT

The speed of human walking is a valuable indicator of individuals' health status, for example in sports or medicine. Classic methods such as the camera-based approach have serious limitations: (1) they can be used only in the laboratory setting, and (2) the computational complexity of the data processing is remarkably high.

The development of small wearable inertial sensing systems and suitable methods of data processing allow the analysis of human motion to be performed outside the laboratory. Moreover, such solutions can work in the real-time regime.

Unfortunately, the inertia-based human walking speed estimation systems applying the strap-down integration approach have an unavoidable drawback. The disadvantage is the estimation inaccuracies caused by the accumulation of errors. This paper presents an approach for attenuating these errors by applying a method for estimating drift.

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1. Introduction

Human locomotion is a topic of interest in research areas such as clinical studies [1], sports training (both professional and recreational) [2], and medicine [3]. The characterization of human locomotion may differ in specific areas of research. In general, there are two main approaches: temporal and spatial. For example, in the analysis of human walking, parameters such as stride length or frequency, gait asymmetry, and walking speed are applied [4,5]. In this study, we focus our efforts on walking speed.

The most popular approach for estimating instantaneous walking speed is a method making use of a camera-based tracking system (for example OptiTrack, Vicon, or BTS Bioengineering). Unfortunately, most such systems are expensive, and they can be employed only in a laboratory setting. Moreover, the approach used has an influence on the values determined for the parameters of human walking and, in consequence, on the results of motion analysis that are performed based on these parameters.

Recently, an alternative to the camera-based tracking system, i.e. micro-electromechanical devices, has become increasingly popular. The idea of applying micro-electromechanical devices (MEMs for short) in human motion analysis is not new, but it is attracting attention because of improved performance and affordable prices [6]. Moreover, the application of MEMs in human motion analysis aids in overcoming the drawback of camera-based tracking systems, i.e. the lack of mobility. This is possible because advancements in micro-electromechanical devices allow the design and manufacture of wearable systems.

Wearable systems for the analysis of human motion are usually composed of triaxial inertial sensors such as the accelerometer and the gyroscope. Some systems have an additional sensor, i.e. the triaxial magnetometer. The local magnetic field sensor helps to improve the overall performance of the MEMs devices [7].

According to [5], the following are the groups of methods used to estimate human walking speed:

– model-based;
– machine-learning-based;
– signal-based.

The model-based (MB) methods incorporate biomechanical models of human motion, for example models describing the kinematics of walking. The walking speed is estimated by combining the model with acquired data [8,9].

The machine-learning-based (MLB) methods are a relatively new concept in the field of walking speed estimation. In [5], the authors discuss the possible use of MLB methods for modeling human movement. One of the main problems is related to design-

* Corresponding author.
E-mail address: Krzysztof.Brzostowski@pwr.edu.pl

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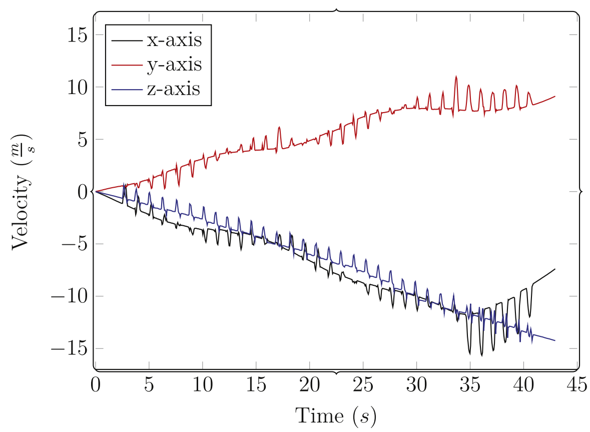

Fig. 1. Illustration of drift in velocity.

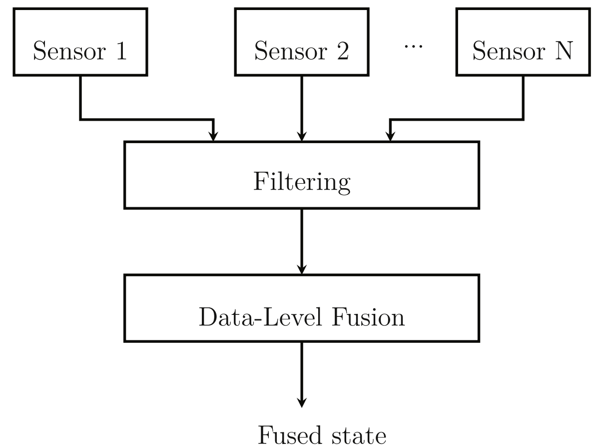

Fig. 2. Data-level fusion (based on [22]).

ing the training datasets. Solutions based on machine learning can perform poorly when the training datasets do not contain all data generated during analyzed activities, e.g. walking. Moreover, because of non-linearities in the object and the non-stationarity of the object, the generalization capabilities of machine learning methods as applied to walking speed estimation may be hard to overcome.

The signal-based methods rely on the strap-down integration (SDI) approach. The SDI method calculates the linear velocity by adding the currently estimated linear velocity to the previously estimated linear velocity. The linear velocity is estimated based on integration of the linear acceleration. The linear acceleration is obtained from a triaxial accelerometer and a triaxial gyroscope; i.e. the angular velocity from the gyroscope is used to determine the quaternion, and then the acceleration is rotated from the body frame to the navigation frame by applying the quaternion to obtain the linear acceleration. The acceleration and angular velocity measurements are usually acquired from an inertial measurement unit (IMU) sensor.

The typical IMU sensor contains the accelerometers, the gyroscopes, and the magnetometers. The velocity is estimated by applying data fusion methods on the measurements acquired from the IMU sensor.

The main drawback of this approach is the tendency of the inherent errors to grow over time [10,11]. This effect is called drift (see Fig. 1), and it is a result of the numerical integration of the noised measurements.

The zero-velocity update (ZUPT) method [12] is one of the methods for dealing with the drift effect. The idea of ZUPT is based on the observation that some human movements, such as walking, are cyclic. Thus, the drift is mitigated by cyclic zeroing of the estimated walking speed when the foot is flat on the ground (the zero-velocity assumption). Unfortunately, this method has some limitations. The main restriction is that it is only applicable for walking. The method cannot work properly for e.g. running because of the lack of a zero-velocity phase [13]. The other limitation is the problem of detecting the zero-velocity phases. It is a crucial problem affecting the overall quality of the human walking speed estimation [13].

The drawbacks of the ZUPT method have forced researchers to propose alternative solutions. The paper [14] introduced an improved ZUPT approach. The main novelty of the method proposed is the correction of the acceleration measurements before the numerical integration to obtain velocity. Although the error mitigation in the acceleration measurements significantly improves the velocity estimation, there is still the problem of velocity estimation for long distance tracking.

A different idea was proposed in [15,16]. In these studies, the velocity estimation was improved by high-pass filtering. The authors used Butterworth filters to mitigate the numerical integration drift. The drawback of this approach is the problem of determining the cut-off frequency.

In this paper, we propose a new approach based on the idea of drift cancellation from estimated velocity that was proposed in [15,16]. Unlike the approach based on Butterworth filtering, our proposed method is based on piecewise polynomial estimation of the drift. The general idea is to divide the signal into non-overlapping segments and estimate the drift separately in each part. The final drift is the concatenation of the drifts determined in each segment.

As the proposed approach is an alternative to the ZUPT method, in the performance analysis we compare the outcomes of the proposed method with the results from the ZUPT approach which are assumed to be the references. To evaluate the performance of our approach, we used root mean square error (RMSE) and signal-to-noise ratio (SNR). The obtained results demonstrate high agreement between the reference results and the proposed approach.

One of the main elements of the proposed approach is data fusion. The approach is applied to estimate the current velocity based on the measurements acquired from IMU sensors.

Data fusion

Data fusion is the capability of processing and combining data acquired from objects having different natures. The aim is to produce an improved or more comprehensive description of the object of interest [17–19].

In [20], a three-level categorization of multi-sensor systems is proposed. The first level is called *data-level fusion*. Here, data fusion means the combining of raw data acquired from different sensors. The aim is to achieve improved accuracy of object descriptions compared to descriptions using data from a single sensor.

The second level is *feature-level fusion*. The feature level applies when the measurements originate from heterogeneous sources. At this level, some features are extracted from the raw data to create a description of the object of interest. The description usually has the form of a multidimensional feature vector.

The third level is *decision-level fusion*. At this level, data from the first level and the vector of features originating from the second level are combined with high-level domain-specific information [21].

In this paper, we apply the first type, data-level fusion. We present the general model at this level in Fig. 2.

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