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Kinematics based sensory fusion for wearable motion assessment in human walking

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ABSTRACT

Measuring the kinematic parameters in unconstrained human motion is becoming crucial for providing feedback information in wearable robotics and sports monitoring. This paper presents a novel sensory fusion algorithm for assessing the orientations of human body segments in long-term human walking based on signals from wearable sensors. The basic idea of the proposed algorithm is to constantly fuse the measured segment's angular velocity and linear acceleration via known kinematic relations between segments. The wearable sensory system incorporates seven inertial measurement units attached to the human body segments and two instrumented shoe insoles. The proposed system was experimentally validated in a long-term walking on a treadmill and on a polygon with stairs simulating different activities in everyday life. The outputs were compared to the reference parameters measured by a stationary optical system. Results show accurate joint angle measurements (error median below 5°) in all evaluated walking conditions with no expressed drift over time.

1. Introduction

Wearable robotics and monitoring in sports are two recently developed fields where the latest progress in sensory technology contributed essentially. Introduction of micro-electromechanical systems (MEMS) components enabled production of miniature, low power, and inexpensive sensors. MEMS components are convenient to be worn by the user [1] or to be implemented on a wearable robotic structure, such as active prostheses [2,3], orthoses [4,5], and exoskeletons [6,7]. Wearable sensory system is ought to provide information on kinematic (e.g. joint angles) and kinetic (e.g. feet reactions) parameters. The acquired information is used for providing the feedback to the user [8–10] or for closing the loop in a robot controller [4,11–13].

Level-ground human walking is considered a basic manoeuver of human locomotion and as such has been subject of numerous studies in recent decades [14,15]. The algorithms for on-line processing of the sensory signals have been evolving together with growth of computational power on microcontrollers and knowledge about mechanisms of walking. In the first attempts, the uni-axial gyroscopes attached to body segments were used to assess joint angles with a simple integration method [16–19]. The method is prone to the output drift over long-term measurements since it integrates superimposed noise over time. To overcome the problem of drift a solution was proposed as a system reset and re-initialization of the outputs with regards to a known reference value at each gait cycle [16]. In [17,18] authors introduced additional accelerometers to determine the mid stance phase in each stride and to estimate an inclination of the segment.

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Nomenclature

$\boldsymbol{a}_\mathrm{A}$	linear acceleration of point A
$\boldsymbol{a}_\mathrm{B}$	linear acceleration of point B
$\boldsymbol{\omega}$	angular velocity
$\boldsymbol{r}_\mathrm{AB}$	position vector connection A to B
${}^\mathrm{I}\boldsymbol{\omega}$	angular velocity measured by IMU
${}^\mathrm{I}\boldsymbol{a}$	linear acceleration measured by IMU
${}^\mathrm{I}\mathbf{B}$	magnetic field measured by IMU
${}^\mathrm{E}\boldsymbol{a}_1$	linear acceleration of the previous joint
${}^\mathrm{E}\boldsymbol{a}_2$	linear acceleration of the following joint
${}^\mathrm{S}\boldsymbol{r}_1$	vector between previous joint and IMU
${}^\mathrm{S}\boldsymbol{r}_2$	vector between IMU and following joint
${}^\mathrm{S}\boldsymbol{g}$	gravity vector
${}^\mathrm{S}\boldsymbol{q}_\mathrm{I}$	quaternion describing IMU's orientation in segment's coordinate frame
${}^\mathrm{S}\boldsymbol{a}_\mathrm{DYN}$	dynamic acceleration
${}^\mathrm{E}\boldsymbol{q}$	quaternion describing the segment's orientation
${}^\mathrm{E}\mathbf{B}$	Earth's magnetic field
${}^\mathrm{E}\boldsymbol{q}(0)$	quaternion describing initial segment's orientation
${}^\mathrm{S}\mathbf{B}(0)$	initial magnetic field
${}^\mathrm{E}\mathbf{R}(0)$	rotation matrix describing initial segment's orientation in Earth's frame
${}^\mathrm{S}\boldsymbol{a}(0)$	initial linear acceleration
$\boldsymbol{f}$	function relating two sequential state vectors
$\boldsymbol{h}_k$	function relating the state to the measurement
$\boldsymbol{x}_k$	state vector
$\mathbf{z}_k$	measurement vector
$\boldsymbol{u}_{k-1}$	input vector
$\boldsymbol{w}_{k-1}$	process noise
$\boldsymbol{v}_k$	measurement noise
${}^\mathrm{E}\dot{\boldsymbol{q}}$	first time derivative of quaternion ${}^\mathrm{E}\boldsymbol{q}$
${}^\mathrm{E}\ddot{\boldsymbol{q}}$	second time derivative of quaternion ${}^\mathrm{E}\boldsymbol{q}$
Δt	time difference
$\mathbf{P}_k^-$	error covariance
$\mathbf{A}_k$	Jacobian matrix of the $\boldsymbol{f}$ with respect to $\boldsymbol{x}$
$\mathbf{Q}_k$	process noise covariance matrix
$\mathbf{W}_k$	process Jacobian matrix
$\mathbf{K}_k$	EKF gain matrix
$\mathbf{H}_k$	Jacobian matrix of the $\boldsymbol{h}$ with respect to $\boldsymbol{x}$
$\mathbf{R}_k$	measurement noise covariance matrix
$\mathbf{V}_k$	measurement Jacobian matrix
${}^\mathrm{S}h_1$	height of the IMU placement on the foot
${}^\mathrm{S}\mathrm{COP}_{\mathrm{X},1}$	COP in the X direction
${}^\mathrm{S}\mathrm{COP}_{\mathrm{Z},1}$	COP in the Z direction

The inclination estimate was then used to reset the integration of angular velocity. Mayagoitia et al. [19] used accelerometers under static conditions to assess the reference angle needed for the calculation of segmental orientation. Difficulty with this approach is that during fast uninterrupted walking it is impossible to accomplish accurate re-initialization. Besides, this approach is not suitable for real-time applications due to computationally demanding algorithms.

The problem of the integrational drift can be also avoided by using only accelerometers for joint angle assessment. Presented methods [20,21] do not implement the integration of angular velocity but are built upon comparison of accelerations at the center point of rotation obtained from sensors placed on two adjacent segments. Willemsen et al. [20] calculated joint angles using data from pairs of two uniaxial accelerometers in two dimensions. Authors stressed that angle error increases with increasing the speed of motion. Dejnadabi et al. [21] presented a methodology of utilizing a combination of accelerometer and gyroscope per segment. The approach estimates the acceleration of the joint center by virtually placing a pair of sensors at the rotation center. Authors split the motion of the individual segment into linear and angular motion and thus utilize relation between acceleration and angular velocity. Joint angle is determined by comparing the acceleration of the rotational point expressed in adjacent segments and considering the rotation between the segments. The accuracy of the algorithm is conditioned with the anatomical aspect of the individual subject. In [22] authors introduced an array of accelerometers mounted on a rigid rod. The angle of individual segment is determined by band pass filtering of the difference between measured accelerations from two sensors. Experimental validation of the algorithms was accomplished only at low speeds of walking (below 2 km/h) with obtained accuracy below 6°. Similar approach was presented by Liu et al. [23] as double-sensor difference based method utilizing two accelerometers per segment for orientation estimate. The difference between two sensors mounted on the same segment is expressed only with the rotational acceleration while the gravitational and linear accelerations, skin motion artifact, and other noise are eliminated when measured acceleration data are mutually subtracted.

Luinge and Veltink [24] introduced the use of Kalman filter for assessing the orientation of individual segment by fusing data from gyroscope and accelerometer. The orientation estimate obtained by integration of the 3D angular velocity is continuously corrected by using inclination estimate obtained from measured acceleration of the segment. The results show that due to the heading drift the presented method is not suitable for long-term measurements. Also the performance of Kalman filter is significantly reduced when estimating the orientation of fast moving segment [25]. Similar, Favre et al. [26] presented quaternion-based fusion of gyroscope and accelerometer data. The correction of the integrated segment's orientation was performed by estimating inclination angle via accelerometer when the segment was not undergoing fast motion. Presented method is accurate only for a short time motion assessment. In [27] authors used angular velocity to differ between translational and gravitational component in measured acceleration. The orientation of the segment is determined by assessing the inclination from resultant acceleration. Authors stated that gait at higher velocities influence the accuracy considerable and that sensor placement must be taken into consideration.

Common to the methods above is that they operate with respect to one reference axis which is gravity. With this technique only segment's orientation in two dimensions can be determined. To measure three-dimensional orientation,