A real-time gait measurement system for wearable ankle-foot assistive device

Lin Meng, Uriel Martinez-Hernandez, Craig Childs, Abbas A. Dehghani-Sanij and Arjan Buis

Abstract—Wearable robotics is a promising approach for assistance to people with gait deficits. The efficient sensory feedback is of important for closing the system loop of adaptive robotic control. This work presents a novel real-time gait measurement system for ankle-foot assistive device based on data from wearable sensors. This system incorporates two inertial measurement units (IMUs) attached to the shank and foot respectively. Recognition of gait stance and swing phases is performed by a high-level probabilistic method using angular rate from the IMU attached to the shank. The ankle planar-/dorsiflexion angle is measured by fusing the measured angular rate and acceleration from the two sensors based on a complimentary filter algorithm and sensor-to-segment identification method. The proposed system was experimentally validated in real-time while 10 healthy subjects walking on the treadmill with three different speeds. The outputs were compared to the reference measured by a Vicon motion capture system. Results show that the Bayesian recognition method achieves the recognition of gait phases with an accuracy above 94% and a delay response time below 20ms and accurate IMU-based angle measurements (RMSE below 3.5°). The results demonstrate the potential of the wearable system for perception in the robotic control of ankle-foot assistance.

Index Terms—inertial measurement units, gait analysis, gyroscopes and accelerometers, gait phase recognition, ankle angle measurement, hierarchical structure, sensor data fusion

I. INTRODUCTION

STROKE, brain injury, spinal cord injury and other neurological diseases usually result in locomotion deficits, such as drop foot gait. An individual with a drop foot suffers from a limited ability to lift the foot during early swing phase. It would lead to a pathological gait with a high risk of tripping and falling [1] and have a negative impact on the persons’ independence to perform activities of daily living, which would influence their quality of life. An ankle-foot assist device is usually a wearable medical device that is attached to the wearer’s ankle and foot, aiming to provide a certain amount actuation for the correction of drop foot.

To maximise the efficiency of gait interventions, real-time information presenting the movement need to be explored. The real-time gait feedback that highly correlated to the use of the system would augment proprioceptive inputs synchronised with the gait cycle [2], [3].

Most devices for drop foot correction depend on simple and fixed pattern control where gait events switch on/off the external assistance, making these robots susceptible to failure during the assistance to human [4]. These systems realise the automatic identification of gait events using various sensors, such as foot pressure insoles, foot switches, inertial measurement units (IMUs), electromyography (EMG) signals and etc. A simple approach involving foot switches or force sensitive resistors (FSRs) to detect the foot contact provided satisfactory results for healthy subjects. However, foot contact sensors can not provide any information during swing phase and the sensor reliability reduces when subjects have drop foot or shuffling gait [5], [6]. A combination of the inertial sensors and foot sensors increased the number of gait phases [5] as the IMUs provide sufficient information correlated to locomotion, especially for the swing phase. The IMUs have been popularly adopted in ambulatory systems due to their small size, low cost and low power consumption. The use of either whole IMU consisting of gyroscopes, accelerometers and magnetometers or parts of it to determine kinematic data [7], activity recognition [8] or gait event classification [9], [10] has shown promising results.

A robust human-machine interaction is of importance for the development of assistive devices used for daily life assistance. Real-time modulation requires sensory system providing the feedback for closing the loop in a robot controller [11], [1]. Kinematics (e.g. joint angles) are important for advanced control of wearable robotics. However, few studies have applied an inertial sensor system for both gait phase detection and kinematic measurement. This study firstly aimed to develop a robust wearable gait measurement system using a small number of inertial sensors for joint angle measurement and gait phase detection simultaneously during gait.

The rest of this paper is organised as follows: the related work is presented in Section II. The proposed method is presented in Section III. The experiments and results are described in Section IV. The discussion and conclusions are given in Section V.

II. RELATED WORK

Machine learning offers sophisticated algorithms for developing robust and adaptable system for perception. Artificial
neural networks (ANN), fuzzy logic (FL) and hidden Markov models (HMM) were often applied in the detection of gait phases [12], [10], [13], [14]. Williamson et al. [12] applied an adaptive logic network to a cluster of accelerometers attached to the shank for gait phases detection. Taborri et al. [14] proposed a weighted HMM that realised gait phases recognition utilising angular rates of the foot, shank and thigh. The methods require a network of sensors and produce black box models, making data synchronisation and collection and real-time implementation a complicated process. Probabilistic approaches provide well-defined mathematical models to develop reliable systems for perception. Yuwono et al. [15] presented a single IMU system that identifies bilateral heel-strike events with the use of Bayesian method. Uriel et al. [8] proposed a Bayesian formulation to achieve high recognition accuracy of simultaneous daily activities and gait phases recognition with small number of sensors.

An key problem on measurement of joint angles using inertial sensors is drift resulted by error accumulation after time integration. Several methods have been proposed to eliminate the drift: strap-down method [16], [17], high-pass filtering [18]. Morris et al. [16] set the signal equal at the begin and end of every gait cycle. Sabatini et al. [17] proposed a method that calculates body segment orientation from the angular velocity data and compensate the drift with the cycle properties. Tong et al. [18] derived the knee angle from segment angular velocities and applied a low-cut high-pass filter to remove the low-frequency component. Sensor fusion method seems a promising solution for the drift problem. The methods, such as Kalman filter [19] and complimentary filter [7], [20], could correct offset drift at each time online. Sensor orientation can be presented as a quaternion calculated from 9D IMU data and the joint angle is derived from the relative orientation of two adjacent segments [21], [22]. The use of magnetometer measurement where magnetometer disturbances occur may limit the algorithm accuracy and its indoor application. Favre et al. [23] proposed to use acceleration data to compensate the drift from the angular velocity angle. Complimentary filter is relatively simple and easy to be applied in real-time applications. The sensor fusion of gyroscopic-based and accelerometer-based angles has shown its good performance in gait analysis [7], [20].

Human joint angle is quantified on the basis of the international society of biomechanics (ISB) recommends [24]. Due to the complexity of human joint anatomy, it is difficult to align IMU local axes parallel with the joint axes. The data from inertial sensors should be transformed into joint-related coordinate system. The sensor-to-segment orientation and placement can be measured manually, but in 3-dimensional space, it is a cumbersome task that yields low accurate results [25]. Functional calibration has been proposed in which functional motions (e.g. flexion/extension) are employed to find the local coordinates of joint-related axes [7], [26]. Seel et al [7] presented a sensor-to-segment identification approach to determine the local joint axes and position coordinates by exploring the kinematics of the joint from arbitrary motions. The calibration approach does not require precise placement of sensors attached to the body making the system more robust and practical for wearable applications.

For closing the loop of robotic control in ankle-foot assistance, this work proposed a novel real-time gait measurement system consisting of a two-level hierarchical model. The high-level realises recognition of stance and swing phases with the use of a probabilistic method. The low-level calculates the ankle plantar-/dorsiflexion angle based on the acceleration and angular rate data whilst the local joint axes are identified in the functional calibration. The wearable gait measurement system and details of the model are described in Section III.

III. METHODS

Fig. 1A shows the structure of the system model consists of two layers. IMU sensors are attached to the shank and foot. Gait stance/swing phases are detected in the high-level layer with Bayesian algorithm whilst ankle plantar-/dorsiflexion angle is calculated in the low-level layer.

A. High level - gait phase recognition

Recognition of gait phases is performed with a Bayesian formulation together with a sequential analysis method as
shown in Fig. 1B. This probabilistic approach iteratively accumulates sensor data, reducing the uncertainty from sensors measurements. The sequential analysis method, which uses a belief threshold parameter, allows the recognition method to decide whether the information accumulated is enough to make a decision.

1) Bayesian update: The Bayesian method updates the posterior probability by multiplying the prior and likelihood distributions. Sensor measurements and perceptual classes are represented by \( \omega \) and \( c_n \), respectively, where \( n \) is the number of gait phases; stance and swing phases. The Bayesian update process is as follows:

\[
P(c_n|\omega_t) = \frac{P(\omega_t|c_n)P(c_n|\omega_{t-1})}{P(\omega_t|\omega_{t-1})} \tag{1}
\]

where the posterior probability and likelihood at time \( t \) are defined by \( P(c_n|\omega_t) \) and \( P(\omega_t|c_n) \). The prior probability from the previous time \( t-1 \) is defined by \( P(c_n|\omega_{t-1}) \). The measurements \( \omega \) represent the angular velocity signals from the IMU sensors attached to the lower limbs of participants.

2) Prior: Uniform prior probabilities for the gait phases are assumed at the initial time \( t = 0 \), as follows:

\[
P(c_n) = P(c_n|\omega_0) = \frac{1}{N} \tag{2}
\]

where \( c_n \) is the estimated class, \( \omega_0 \) are the sensor measurements at time \( t = 0 \) and \( N \) is the number of gait phases. For time \( t > 0 \) the prior distribution is updated by the posterior estimated at \( t - 1 \), as follows:

\[
P(c_n) = P(c_n|\omega_{t-1}) \tag{3}
\]

3) Measurement model and likelihood estimation: Angular velocity signals from \( S_{\text{sensors}} = 1 \) (attached on the shank) are collected during the walking cycle. The collected signals are used to construct the measurement model with a nonparametric approach based on histograms, which is to evaluate an observation \( \omega_t \), and estimate the likelihood of a perceptual class \( c_n \). This process is performed as follows:

\[
P_t(b|c_n) = \frac{h_{s,n}(b)}{\sum_{b=1}^{N_{\text{bins}}} h(b)} \tag{4}
\]

where \( h_{s,n}(b) \) is the sample count in bin \( b \) for sensor \( s \) over all training data. The histograms are uniformly constructed using \( N_{\text{bins}} = 100 \) intervals. The values are normalised by \( \sum_{b=1}^{N_{\text{bins}}} h(b) \) to have probabilities in \([0, 1]\). The likelihood of the observation \( \omega_t \), by evaluating Equation (4) over all sensors, is estimated as follows:

\[
\log P(\omega_t|c_n) = \sum_{s=1}^{S_{\text{sensors}}} \frac{\log P_t(b|c_n)}{S_{\text{sensors}}} \tag{5}
\]

where \( P(\omega_t|c_n) \) is the likelihood of the observation \( \omega_t \) given a perceptual class \( c_n \). Normalised values in Equation (1) are obtained with the marginal probabilities conditioned from previous sensor observations, as follows:

\[
P(\omega_t|\omega_{t-1}) = \sum_{n=1}^{N} P(\omega_t|c_n)P(c_n|\omega_{t-1}) \tag{6}
\]

4) Decision making: The Bayesian update process stops once a belief threshold \( \beta_{\text{threshold}} = [0.0, 0.1, \ldots, 0.99] \) is exceeded. This action enables the decision making process to estimate the gait phase, using the maximum a posteriori (MAP) estimate, as follows:

\[
\text{if } P(c_n|\omega_t) > \beta_{\text{threshold}} \text{ then } \hat{c}_n = \arg \max \ P(c_n|\omega_t) \tag{7}
\]

where \( \hat{c}_n \) is the estimated gait phase that tells us whether the human is in stance or swing phase during the walking cycle.

B. Low level - gyroscope and accelerometer integrated ankle angle measurement

Fig. 2. The procedure of sensor-to-segment calibration. Three sensors were respectively attached to the thigh, shank and foot. The subject performed knee flexion/extension and ankle dorsifl-int/plantarflexion when angular velocity data were recorded. The joint axis of thigh sensor \( j_1 \) was set based on prior knowledge and the flexion axis of shank \( j_2 \) was estimated during the knee sagittal movement. The ankle axis \( j_3 \) was calculated with the obtained \( j_2 \) during the ankle dorsifl-plantarflexion movement.

1) Identification of the Joint Axis:

\[
\| \omega_1(t) \times j_1 \| - \| \omega_2(t) \times j_2 \| = 0 \tag{8}
\]

Where \( \| \cdot \| \) is the Euclidean norm, the \( j_1 \) and \( j_2 \) are written in spherical coordinates:

\[
j_1 = (\cos(\phi_1)\cos(\theta_1), \cos(\phi_1)\sin(\theta_1), \sin(\phi_1))^T
\]

Where \(-\pi/2 \leq \phi_1 \leq \pi/2, -2\pi \leq \theta_1 \leq 2\pi\). The \( j_1, j_2 \) can be identified using a least square cost function, Eq 9.

\[
C(\phi_1, \phi_2, \theta_1, \theta_2) = \sum_{t=1}^{N} (\| \omega_1(t) \times j_1 \| - \| \omega_2(t) \times j_2 \|)^2
\]

If the proximal segment remains still when the distal segment moves, \( j_1 \) should be set based on prior knowledge and \( j_2 \) is solved by the cost function (Eq 9).

In our study, three inertial sensors are attached to the hip, shank and foot segments respectively as shown in Fig 2. There are no strict rules about locations of the sensors on the segment and their orientations with respect to the segments. It is also assumed that the local sensor axes do not coincides
with the joint axes. The flexion axes of the shank and foot are determined respectively during the knee flexion/extension and ankle dorsif-/plantarflexion movement. MATLAB function *fmincon* is used to solve the cost function *C*. It needs to be noted that the *j*₂ and *j*₃ should point to the same direction.

2) **Joint Angle calculation:** Gravity-based acceleration can be expressed by:

\[ a_g(t) = D(\hat{g}_{aw}(t))G \]  

(10)

Where \( G = (0, 0, 1)^T \) at the global reference frame, \( D \) stands for the direction cosine matrix in the form of \((D_1, D_2, D_3)\) with quaternion \( \hat{q}_{aw}(t) \) [27]. Eq. 10 can be decomposed as:

\[ a_g(t) = D_3(\hat{q}_{aw}(t)) = \begin{pmatrix} -q_2 & q_3 & -q_0 & q_1 \\ q_1 & q_0 & q_3 & q_2 \\ q_0 & -q_1 & q_2 & q_3 \end{pmatrix} \]  

(11)

Its rotation can be represented by the normalised quaternion \( \hat{q}_{aw}(t) \) that is calculated through acceleration and angular rate data fusion at the time instant *t*, see details in Appendix.

An accelerometer-based joint angle can be approximated by the angle between the projections of \( a_g \) into the joint plane, which is defined as following:

\[ \alpha_{acc}(t) = \arctan\left( \frac{v_2 \times v_3}{v_2 \cdot v_3} \right) \]  

(12)

Where \( v_2 = (a_{g,2}(t) \cdot x_2, a_{g,2}(t) \cdot y_2, 0)^T \), \( v_3 = (a_{g,3}(t) \cdot x_3, a_{g,3}(t) \cdot y_3, 0)^T \). The joint plane is defined by a pair of axes \( x_i, y_i \in \mathbb{R}^3 \):

\[ x_2 = j_2 \times c, y_2 = j_2 \times x_3 \]

\[ x_3 = j_3 \times c, y_3 = j_3 \times x_3 \]  

(13)

c is an arbitrary normalised vector that is not parallel to the axes \( j_2 \) and \( j_3 \).

A gyroscope-based joint angle is calculated by the integration of the difference of the angular velocity around the joint axis:

\[ \alpha_{gyr}(t) = \int_0^t (\omega_2(\tau) \cdot j_2 - \omega_3(\tau) \cdot j_3) d\tau \]  

(14)

The gyroscope-based angle is precise on the short time scales, but exhibits slow drift in long time measurement. The accelerometer-based angle is not affected by drift, but it is sensitive to the measurement noise and may be not reliable at the moments when large acceleration change occurs. A complimentary filter is used to combine two angles in order to remove the drift in the gyroscope-based angle. An implementation of the complimentary filter is given by [7]:

\[ \alpha(t) = \lambda_\alpha_{acc}(t) + (1-\lambda)(\alpha(t-\Delta t) + \alpha_{gyr}(t) - \alpha_{gyr}(t-\Delta t)) \]  

(15)

### C. Real-time protocol

The pseudocode of the real-time gait measurement system is given as follows in Table I.

**TABLE I**

**PROPOSED GAIT MEASUREMENT ALGORITHMS WITH ACCELERATION AND ANGULAR RATE INPUTS IN REAL-TIME PROGRAM**

<table>
<thead>
<tr>
<th>Initialisation:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t = 0 ), ( f = 148 ), ( \Delta t = \frac{1}{f} ), ( \beta_{\text{threshold}} = 0.99 ), ( \hat{q}<em>{aw, i\text{init}} = (1, 0, 0, 0)^T ), ( \lambda = 0.05 ), ( d = 0.05 ), ( d</em>{\text{avr}} =</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>while no stop commands and new acceleration and angular rate data input received do</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) <strong>High Level</strong></td>
</tr>
<tr>
<td>2) Input: ( \omega_2 )</td>
</tr>
<tr>
<td>3) Calculate the likelihood ( P(\omega_2</td>
</tr>
<tr>
<td>4) Update the posterior ( P(c_n</td>
</tr>
<tr>
<td>5) if ( P(c_n</td>
</tr>
<tr>
<td>6) Go to step 9 to return the estimated class</td>
</tr>
<tr>
<td>7) else update the prior ( P(c_n) = P(c_n</td>
</tr>
<tr>
<td>8) Go to step 1 to collect more sensor data</td>
</tr>
<tr>
<td>9) Output: ( \hat{c}_n )</td>
</tr>
<tr>
<td>10) <strong>Low Level</strong></td>
</tr>
<tr>
<td>1) Input: ( a_{g,2}, a_{g,3}, \omega_3 )</td>
</tr>
<tr>
<td>2) ( t = t + 1 ), ( a_1 = \frac{</td>
</tr>
<tr>
<td>3) ( \hat{q}<em>{aw}(t) = \left{ I + \frac{(1-\lambda)\Delta t}{2} (v_1 \times + \gamma W</em>{a-\omega} t) \right} \hat{q}_{aw}(t-1) )</td>
</tr>
<tr>
<td>4) ( \hat{q}<em>{aw}(t) = q</em>{aw}(t_1) )</td>
</tr>
<tr>
<td>5) ( a_{gyr}(t) = D_3(\hat{q}_{aw}(t)) )</td>
</tr>
<tr>
<td>6) ( v_1 = [a_{gyr} \cdot x_1, a_{gyr} \cdot y_1, 0]^T ), where ( x_1 = j_1 \times c, y_1 = j_1 \times x_1 )</td>
</tr>
<tr>
<td>7) ( \alpha_{acc} = \Delta(v_2, v_3) )</td>
</tr>
<tr>
<td>8) ( \alpha_{gyr} = b_{aw}(10) + (\omega_2 \cdot j_2 - \omega_3 \cdot j_3) \Delta t )</td>
</tr>
<tr>
<td>9) ( \alpha = \lambda_{\alpha_{acc}} + (1-\lambda)(b_{aw}(10 - d_{aw}) + \alpha_{gyr} - b_{aw}(10 - d_{aw})) )</td>
</tr>
<tr>
<td>10) Update buffers ( b_{aw} ) and ( b_{gyr} )</td>
</tr>
<tr>
<td>11) Output: ( \alpha )</td>
</tr>
<tr>
<td>end while</td>
</tr>
</tbody>
</table>

### IV. EXPERIMENTS AND RESULTS

#### A. Experiment Set-up

The study was approved by the ethics committee of the Department of Biomedical Engineering at the University of Strathclyde. Ten subjects (six males and four females, age = 26.5 ± 6.2 years) participated in this study. Each subject wore six TrignoTM IM sensors (Delsys Inc., USA) which were respectively attached to the thigh, shank and foot of both legs. To validate our real-time gait measurement system, the subject also wore a marker set of Strathclyde functional cluster model, Fig 3. A 12 camera Vicon motion capture system (Vicon MX Gigante, Oxford Metrics Ltd., UK) was used as reference. Marker trajectories were recorded at 100Hz. IMU and stereophotogrammetric data streams were synchronised via an audio signal of START button clicking.

Each subject was instructed to perform knee flexion/extension and ankle dorsif-/plantarflexion in the calibration trial (Fig 2). Each movement was executed with a repetition of ten times. The joint axes were calculated using the method in section III-B1 and saved as a *MAT* file. Subsequently, the subjects walked on the treadmill at various speeds (0.5, 1.0 and 1.5 m/s) for 1 minute respectively. The gait measurement system generated the ankle angle and gait phase detection results while the marker trajectories were gathered. Reference of kinematic outputs and gait phases were post-processed using MATLAB-Nexus interface model (MATLAB 2017b, MathWorks, Natick, USA).
Actual gait phases

Estimated gait phases

Gait events can be further defined during the gait cycle in which heel-strike (HS) is the transition from the swing to stance and toe-off (TO) is the transition from the stance to swing. The time difference between the HS and TO detection and the reference were checked offline as shown in Fig 5. Most of the difference were within the mean ± 1.96 SD lines, illustrating good agreement between the gait events detection and the optical reference. Higher variation in the difference was observed with the speed of 0.5 m/s.

C. Accuracy of ankle angle measurement

Typical ankle angle estimated from the IMU data and reference for different speeds is shown in Fig 6A. The error was defined as the difference between the angles obtained from the proposed algorithm and Vicon reference. The Fig 6B shows the estimated errors of the trial in Fig 6A. It can be seen that the accuracy decreases when the speed increases.

The accuracy of the algorithm was evaluated in terms of the root-mean-square error (RMSE), offset and Pearson’s correlation coefficients (PCC) between the Vicon reference and angles provided by the proposed method. PCC results in Table II shows that the estimated angle using IMU data for the entire dataset had a good agreement with the reference. The RMSEs of the ankle angle are given in Table II, along with the offsets. It is observed that the RMSEs as well as the offsets increased as the speed increased. The offset in ankle angle estimation was caused by the lateral movement of foot segment on the treadmill during the stance phase [28]. The loss of accuracy may be caused by the increase in dynamics and duration of measurement. Our algorithm had a stable performance in angle measurement using a complimentary filter as shown in Fig 6A, so the decrease of the accuracy is likely to be due to the walking speed.

V. DISCUSSION AND CONCLUSION

This paper proposed a novel gait measurement system that can be used for automatic feedback control of wearable drop-foot assistance devices. A hierarchical model structure was firstly proposed to provide simultaneously gait phases recognition and ankle plantar-/dorsiflexion angle. The use of Bayesian algorithm and sensor-to-segment calibration does not require the precise placement of sensors on the segments and thus improves its robustness of practical implementation. The proposed system provides good accuracy for both gait phase detection and ankle angle compared to optical system reference.

Most current systems focused on precise gait phase recognition [10], [29], [13], [12], [30] while the detected gait event was used as a reliable trigger to start the stimulation. Seel et al.[1] measured foot pitch angle and four gait phases by placing a 6D IMU on the foot, and based on which an iterative learning control scheme was developed. Results showed that the close-loop approach would facilitate the adaptation from patient to patient. A multilayer architecture is recognised to be essential for intelligent systems to perform robust data processing, perception and action at different levels of abstraction [8]. Our work could be extended to include high- and low-level process of robotic control in real-time.

Studies determined the most common gait phases (stance and swing) [9], [29], [13], [15] and some also focused on additional phases [12], [31], [32], [10], [30], [14]. The detection accuracy for IMU and gyroscope based systems was higher than systems based on accelerometers. Acceleration data is easily affected by disturbance (such as heel-strike) and thus requires complex signal processing to extract gait features [13]. Sensor positions were various in studies while they can be placed on the waist, thigh, shank or foot. Taborri et al.[14]...
Fig. 5. The time difference between the heel-strike (HS) and toe-off (TO) gait event detection and the reference from the optical system at various speeds (0.5 m/s, 1.0 m/s, 1.5 m/s).

![Graphs showing time difference between gait event detection and reference](image)

Fig. 6. (A) Comparison of ankle angle estimates using IMU data (red) and reference optical system (blue) for Subject 1 at three different speeds (0.5 m/s, 1.0 m/s and 1.5 m/s). (B) Ankle angle estimation error from IMU data and reference for Subject 1 at three different speeds.

![Graphs showing ankle angle comparison and error](image)

showed the best location for a gyroscope is on the foot and Bejarano et al.[9] reported the same accuracy obtained by a single IMU placed on the shank. Sensors attached to the shank and foot leads to the highest accuracy and the shortest time delay [10], [12], [30], [13], [32].

The performance of the Bayesian method was analysed with the recognition of gait phases. The gait cycle was segmented into the stance and swing phases, which were successfully recognised with an accuracy of 97.85% and 96.27%, respectively at the speed of 1 m/s. The performance of recognition was slightly affected by the factor of walking speed as shown in Fig.4, which may be related to walking speed in training dataset. Despite this reduction in accuracy, the recognition method is robust considering that the algorithm was not re-trained with data from new subjects. Previous works, using a variety of machine learning algorithms and sensor sets have

<table>
<thead>
<tr>
<th>Treadmill speed</th>
<th>Offset (deg)</th>
<th>RMSE (deg)</th>
<th>PCC</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5m/s</td>
<td>-0.38 ± 2.05</td>
<td>2.39 ± 0.37</td>
<td>0.94 ± 0.03</td>
<td>0</td>
</tr>
<tr>
<td>1.0m/s</td>
<td>4.46 ± 3.57</td>
<td>2.86 ± 0.65</td>
<td>0.92 ± 0.03</td>
<td>0</td>
</tr>
<tr>
<td>1.5m/s</td>
<td>7.28 ± 4.39</td>
<td>3.24 ± 0.67</td>
<td>0.90 ± 0.04</td>
<td>0</td>
</tr>
</tbody>
</table>
been able to achieve accuracies of 91%, 99% and 100% [12], [9], [30], [15]. However, they present limitations such as fixed sampling window size, large number of sensors, black box models and the need of algorithm re-training for new subjects. Delay time in real-time systems with sophisticated machine learning algorithms was over 35ms [29], [32], [30]. A simple state machine learning method achieved a shorter decision delay time of 23 ms [10]. Our Bayesian formulation with a sequential analysis method obtained a response time of less than 20ms (Figure 5). The method was able to react fast and high accuracy to distinguish gait phases with the use of a single IMU sensor attached to the lateral side of the shank.

A sensor-to-segment calibration procedure was proposed to determine the local joint axis from calibration movements of the joints. The method is more practical and more robust than previous methods that require to attach the inertial sensors in specific positions or orientation [28]. Functional methods are sensitive to the execution of the calibration [26]. To allow the method applied on patients, passive calibration movements should be considered in the future protocol.

We developed a simple but efficient method for estimation of ankle joint angle using a complimentary filter formulation to minimise the effects of drift. The proposed method is based on IMU sensors that consist of accelerometers and gyroscopes. The use of magnetometers is avoided so that it can be used for indoor application. Our method does not need information about the distances to joint centres for calculating accelerometer-based angle as previous work [7], which is a benefit of our algorithm.

PPCs for the ankle angle was in the range from 0.90 to 0.94 and RMSE was within 3.5 degrees for the angle values. The results showed that the quality of angle measurement decreases while the treadmill walking speed increases (Table II). Compared to the knee angle, the ankle angle measurement was more affected by treadmill speed variation [28]. The offset may come from linear displacement of the stance foot on the treadmill and impacts at heel strike. Further work is dedicated to the question how to eliminate or compensate the noise factor.

This work presented a novel gait measurement system for providing sufficient feedback for drop-foot correction control. The device used data from two wearable sensors attached to the shank and foot respectively. A hierarchical architecture consisting of high- and low-level layers, was developed to recognise the gait stance and swing phases and measure the ankle angle. Validation experiment in real-time was systematically performed. The experiment allowed the analysis of recognition accuracy and angle measurement errors while the subjects walked on treadmill with three different speeds. Overall, the results demonstrated that the proposed system offered an efficient approach for perception in the adaptive control of ankle-foot assistance.

APPENDIX A

QUATERNION ESTIMATION WITH ACCELEROMETER AND GYROSCOPE SENSOR FUSION

The 3D angular rate $\omega$ and 3D acceleration $a$ can be defined by

$$\omega = (\omega_x, \omega_y, \omega_z)^T$$
$$a = (a_x, a_y, a_z)^T$$

(16)

The relationship between quaternion and the angular rate is usually described as a differential equation

$$\dot{q}_\omega(t) = \frac{1}{2} (\Omega \times q_\omega(t - 1)) $$
$$= \frac{1}{2} \begin{bmatrix}
0 & -\omega_x & -\omega_y & -\omega_z \\
\omega_x & 0 & -\omega_z & \omega_y \\
-\omega_y & \omega_z & 0 & \omega_x \\
\omega_z & -\omega_y & -\omega_x & 0
\end{bmatrix} q_\omega(t - 1)$$

(17)

The quaternion is therefore calculated through gyroscope integration at the time $t$.

$$q_\omega(t) = q_\omega(t - 1) + \dot{q}_\omega(t) \Delta t$$

(18)

A first order complimentary filter model is used, which introduces the accelerometer to compensate the error of the angular rate.

$$\hat{q}_{aw}(t) = (1 - \gamma) \hat{q}_\omega(t) + \gamma \hat{a}_w(t)$$

(19)

Quaternion incrementation from accelerometer is defined as the following equation. Its calculation is well explained in [27].

$$\Delta q_a = \frac{W_a - I}{2} q_0$$
$$= \frac{1}{2} \begin{bmatrix}
a_x - 1 & a_y & -a_x & 0 \\
a_y & a_x - 1 & -a_y & 0 \\
-a_x & a_y & a_x - 1 & 0 \\
0 & a_y & -a_x & a_x - 1
\end{bmatrix} q_0$$

(20)

The estimation of quaternion calculated through gyroscope and accelerometer fusion can be described as

$$q_{aw}(t) = q_{aw}(t - 1) + \hat{q}_{aw}(t) \Delta t$$

(21)

This equation can be further expressed by substituting Eq 19, 17 and 20.

$$q_{aw}(t) = \hat{q}_{aw}(t - 1) + [(1 - \gamma) \hat{q}_\omega(t) + \gamma \hat{a}_w(t)] \Delta t$$
$$= \hat{q}_{aw}(t - 1) + \frac{1}{2} (1 - \gamma) [\Omega \times] \hat{q}_{aw}(t - 1) + \gamma \Delta q_a$$
$$= \left\{ \left(1 - \frac{\gamma}{2} \right) [\Omega \times] + I \right\} \hat{q}_{aw}(t - 1) + \frac{\gamma}{2} W_a - I \hat{q}_{aw}(t - 1)$$
$$= \left\{ I + \left(1 - \frac{\gamma}{2} \right) [\Omega \times] + \frac{\gamma}{2} W_a - I \right\} \hat{q}_{aw}(t - 1)$$

(22)

Note that a normalisation step is taken after each update.
REFERENCES


Lin Meng received the PhD degree from the division of Biomedical Engineering, University of Glasgow, Glasgow, U.K., in 2016. She is currently an Associate professor at Tianjin International Joint Research Center for Neural Engineering, Academy of Medical Engineering and Translational Medicine, Tianjin University, Tianjin, China. Her research interests include motion analysis, wearable sensing technologies and assistive robotics.

Uriel Martinez-Hernandez received the PhD degree from the Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield, U.K., in 2014. He is currently a Lecturer (Assistant Professor) in Robotics at the Department of Electronics and Electrical Engineering, University of Bath, Bath, U.K. His research interests include touch and vision sensing, wearable assistive robotics, active perception and machine learning for autonomous robots.

Craig Childs received the PhD degree from the University of Aalborg, Denmark. He is currently a Research Fellow at the Biomedical Engineering Department at the University of Strathclyde, Glasgow, UK. He is a Clinical Scientist registered with the HCPC. His research interests include motion analysis, gait stability, virtual reality feedback, wearable sensors and accessibility.

Abbas A. Dehghani-Sanij received the PhD degree from the University of Leeds, Leeds, U.K. He is currently Professor of Bio-Mechatronics and Medical Robotics in the School of Mechanical Engineering at the University of Leeds, Leeds, U.K. His research interests include robotics, biomechatronics, intelligent control, sensors and actuators for the development of intelligent systems/devices. He has published more than 90 journal and conference papers.

Arjan Buis received the PhD degree from the University of Strathclyde. He is currently an Associate professor at the Biomedical Engineering department at the University of Strathclyde, Glasgow, UK. He is a biomedical engineer and Sr. prosthesis & Orthotist. His research interests include the body device interface, wearable sensing technologies, assistive robotics. He has published over 100 journal and conference papers.