# GAIT PHASE DETECTION AND STEP LENGTH ESTIMATION OF GAIT BY MEANS OF INERTIAL SENSORS

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**Abstract: The application of inertial sensors in the FES-aided gait rehabilitation is investigated. Instead of using foot switches, inertial sensors can be applied to detect gait phases. It is shown that it is possible to reliably detect four distinct gait phases by use of inertial sensors. Additionally, foot orientation is estimated by integration of angular velocity. To avoid drift in the orientation estimate a Kalman filter was implemented taking the measured acceleration in the swing phase into account. The foot position during the swing phase of gait can be estimated on the basis of measured acceleration and already calculated orientation. The accuracy of this calculation is increased by introducing start and stop constraints on the velocity. To validate the algorithms described in this paper, two gait trials with stroke patients were performed on a treadmill. In these trials an ultrasonic measurement unit was used as a reference system. The results show that the step length can be estimated quite accurately. The standard deviation of the errors of the step length estimation compared to the reference measurement were lying between 3% and 5 %. The gait phases detection and foot position estimate are expected to be usable in FES-aided gait rehabilitation for stroke patients. The reconstructed position and orientation of the foot can be employed as feedback signals for automatic tuning of muscle stimulation in such systems.**

## Introduction

The impact of stroke on the life of an individual can be dramatic both mentally and physically. Physically the motor control of one side may be deteriorated. Such deteriorated motor functions can be improved by training. Liberson et al. [1] proposed in the sixties to use electrical stimulation to elicit the withdrawal reflex during swing phase of the gait. Since then many systems for Functional Electrical Stimulation have been brought to the market. Most of these systems are using foot-switches to trigger the stimulation depending on whether the foot is on the ground or off the ground. In this paper the possible use of inertial sensors for control in Functional Electrical Stimulation (FES)-gait rehabilitation of stroke patients will be investigated. The miniature inertial sensors which consists of 3 gyroscopes and 3 accelerometers all mounted in orthogonal directions can be used for two purposes, gait phases detection and for the computation of useful gait information such as stride length and foot clearance. Stride length is the distance one foot is covering during one stride, while the foot clearance is the maximum distance in the vertical direction during the swing phase.

Several gait phase detection systems have already been developed. Common for many of these systems is that they detect several gait phases like stance, pre-swing, swing and heel strike [2, 3, 4, 5]. There are many different gait phase definitions but no consistent terminology in literature. In some articles the stance phase is divided into two phases, mid-stance and terminal-stance [4, 5]. The sensors used in these approaches are accelerometers and force sensitive resistors mounted on different positions on the body. Common for these systems is that they enforce rule based approaches to gain the gait phases. In these detection systems, the different gait phases are defined as states of a finite state machine and the transition between states are logic function of the sensory input. Recently, compact miniature inertial sensors have become commercially available and they might be a good alternative to foot switches in the detection of gait phases.

Kotiadis et al. [6] investigated which of the accelerometers and gyroscopes inside the inertial sensor do contribute most to the robust detection of gait phases. Contrary to our work, the sensor was placed at the outer side of the shank just below the knee. If the inertial sensor is attached to the foot, it can also be used to reconstruct the foot movement during a short time frame.


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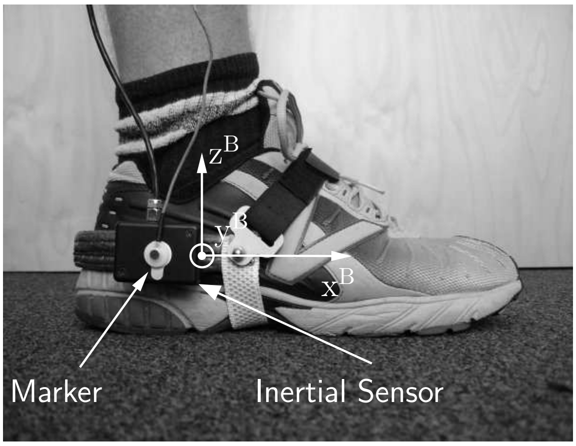


Figure 1: Experimental setup: Inertial sensor and marker of the reference measurement system.

## Methods

*Orientation Estimation*

The sensor used in this research was an inertial measurement unit consisting of three accelerometers and three gyroscopes developed by the Fraunhofer Institute for Factory Operation and Automation (IFF), and the company HASOMED GmbH. By use of this sensor position and orientation can be estimated if the sensor is attached to the foot as pictured in Figure 1. The rotation of the sensor can be found by integration of the angular velocity measured with the gyroscopes in 3 dimensions. The position can then be found by a double integration of the acceleration after it is transformed into a global coordinate system (I).

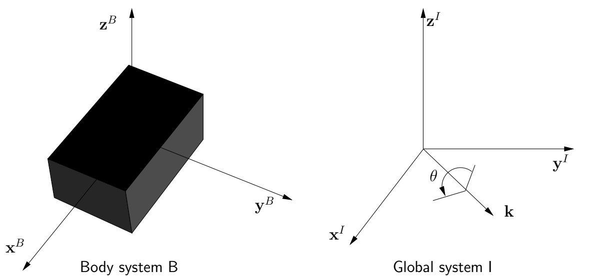


Figure 2: The figure illustrates that the rotation between two coordinate systems can be parameterised by one axis **k** and one angle $\theta$.

The global coordinate system is defined as follows: the z-axis points in the opposite direction of the gravity, the x and y axes are chosen arbitrarily in the orthogonal direction of the z-axis. The coordinate system fixed to the sensor is denoted as B (cf. Figure 2). Orientation can be represented in several ways. Most commonly orientation is represented as Euler angles where orientation is defined by three sequential rotations around primary axes. The disadvantage of this representation is a singularity, a so called gimbal lock. Another possible way to represent the orientation is through an axis-angle parameterisations. The orientation is represented by four parameters, an axis of rotation **k** and an angle of rotation $\theta$. A similar representation are the Euler parameters which are defined as:

$$\eta = \cos(\frac{\theta}{2}) \tag{1}$$

$$\boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix} = \mathbf{k}\sin\frac{\theta}{2} \tag{2}$$

The Euler parameters are put together to a unit quaternion vector

$$\mathbf{q} = \begin{bmatrix} \eta \\ \boldsymbol{\varepsilon} \end{bmatrix} \in R^4, \ \mathbf{q}^T\mathbf{q} = 1 \tag{3}$$

The Euler parameters are subject to the constraint that the norm, the sum of the squares of the elements, is a unity. The quaternions and their algebra were introduced by Hamilton (1844). Orientation in a 3 dimensional space can be represented by a quaternion, and sequential rotations can be represented as quaternion multiplication. Now, assumed that the orientation obtained from integration is biased, then the orientation error can be expressed with quaternion multiplication

$$\tilde{\mathbf{q}} = \mathbf{q}^* \otimes \hat{\mathbf{q}} \tag{4}$$

where $\mathbf{q}$ is the actual orientation, $\hat{\mathbf{q}}$ is the orientation obtained from integration and $\tilde{\mathbf{q}}$ is the error between the two first. The kinematics of the quaternion can verified to be [7]:

$$\begin{aligned} \dot{\hat{\mathbf{q}}} &= \hat{\mathbf{q}} \otimes \frac{1}{2}\begin{bmatrix} 0 \\ \boldsymbol{\omega}^B_{meas} \end{bmatrix} \\ &= \frac{1}{2}\begin{bmatrix} -\hat{\boldsymbol{\varepsilon}}^T \\ \hat{\eta}\mathbf{I} + \mathbf{S}(\hat{\boldsymbol{\varepsilon}}) \end{bmatrix} \boldsymbol{\omega}^B_{meas} \end{aligned} \tag{5}$$

In this equation $\boldsymbol{\omega}^B_{meas}$ is the measured angular velocity in the sensor (B) coordinate system and $\mathbf{S}(\cdot)$ is the cross product operator. Now, even with very good calibrated sensors the obtained orientation from the integration of Equation (5) will drift off after a short time. To compensate for drift an indirect Kalman filter was designed where the error in rotation and a bias of the gyroscope measurement are the estimated states in the Kalman filter. The measured angular velocity is modelled as the sum of the real velocity and a bias

$$\boldsymbol{\omega}^B_{meas} = \boldsymbol{\omega}^B + \boldsymbol{\beta} \tag{6}$$

where $\boldsymbol{\omega}^B$ is the real angular velocity and $\boldsymbol{\beta}$ is a time varying bias. By combining Equations (4) and (5) the error model can be shown to be (deduction is omitted here):

$$\begin{bmatrix} \dot{\tilde{\eta}} \\ \dot{\tilde{\boldsymbol{\varepsilon}}} \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 0 & -(\boldsymbol{\beta})^T \\ \boldsymbol{\beta} & \mathbf{S}(\boldsymbol{\beta}) \end{bmatrix} \begin{bmatrix} \tilde{\eta} \\ \tilde{\boldsymbol{\varepsilon}} \end{bmatrix} \tag{7}$$

By the assumption that the error is small, the approximation that $\tilde{\eta} \approx 1$ can be used. This results in the following


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error dynamics

$$\dot{\tilde{\boldsymbol{\varepsilon}}} = \frac{1}{2}\boldsymbol{\beta} + \frac{1}{2}\mathbf{S}(\boldsymbol{\beta})\tilde{\boldsymbol{\varepsilon}}. \quad (8)$$

The bias in the gyroscope measurements is modelled as a 1st order Markov process

$$\dot{\boldsymbol{\beta}} = -\frac{1}{T_\beta}\boldsymbol{\beta} + \boldsymbol{\xi}_\beta \quad (9)$$

where $T_\beta$ is the time constant of the Markov process. The

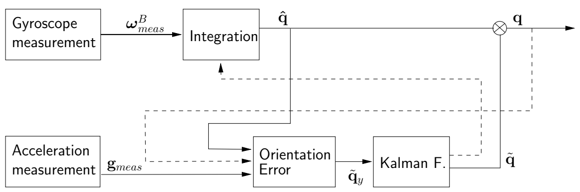


Figure 3: Block structure of the indirect Kalman filter

structure of the orientation estimation is shown in Figure 3. The Kalman filter uses the acceleration measurements as a correction to the already estimated orientation based on integration of the gyroscope measurement. The acceleration measurement can partly give information about the orientation of the sensor, but it does not contain any information about the rotation of the sensor around the z-axis (heading) of the global reference coordinate system. The acceleration measurement can only be used under the assumption that the sensor is not accelerated. Under this assumption the accelerometers are measuring the gravitation vector $\mathbf{g}_{meas}$ . A correction of the orientation estimate using the acceleration measurements is thus only applied in the stance phases of the gait. The corresponding gravitation vector $\hat{\mathbf{g}}$ obtained from the integration is found by this equation

$$\hat{\mathbf{g}} = \hat{\mathbf{R}}^T \mathbf{g}^I \quad (10)$$

where $\mathbf{g}^I = [0\ 0\ 9.81\frac{m}{s^2}]^T$, and $\hat{\mathbf{R}}$ is the rotation matrix corresponding to $\hat{\mathbf{q}}$. The axis of the error rotation goes through the axis orthogonal to the measured gravitation vector as well as the axis orthogonal to the gravitation vector based on the integration. This axis can now be found by applying the cross product between the respecting vectors:

$$\tilde{\mathbf{k}} = \frac{\mathbf{g}_{meas} \times \hat{\mathbf{g}}}{|\mathbf{g}_{meas} \times \hat{\mathbf{g}}|}. \quad (11)$$

Now as the axis of rotation is found, the next step is to find the angle of rotation. This is the angle between the vectors $\hat{\mathbf{g}}$ and $\mathbf{g}_{meas}$ given by this equation

$$\cos(\tilde{\theta}) = \frac{\hat{\mathbf{g}} \cdot \mathbf{g}_{meas}}{|\hat{\mathbf{g}}||\mathbf{g}_{meas}|}. \quad (12)$$

Now the error orientation can be described by a quaternion

$$\tilde{\mathbf{q}}_y = \begin{bmatrix} \cos(\frac{\tilde{\theta}}{2}) \\ \tilde{\mathbf{k}}\sin(\frac{\tilde{\theta}}{2}) \end{bmatrix}. \quad (13)$$

This error quaternion based on the acceleration measurement is used as a measurement update in the Kalman filter. The error state in the Kalman filter will unavoidably grow bigger, and has to be reset at fixed intervals.

*Step Length and Foot Clearance*

By use of the obtained orientation the step length and foot clearance can be estimated through a double integration of the acceleration in the global reference system. The integration is started and stopped at the beginning and the end of every step.

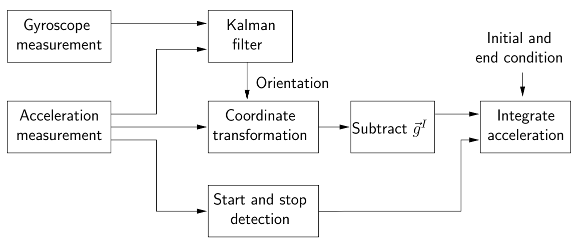


Figure 4: Block diagram of the step length estimation.

In order to improve the accuracy, constraints on the integration are introduced. The velocity of the sensor is assumed to be zero at the beginning and at the end of the movement and the position in the z direction is identical at the beginning and the end. By using these constraints an artificial bias $\boldsymbol{\gamma}$ on the acceleration measurement is introduced. The following measurement equation is used

$$\boldsymbol{a}_{meas} = \boldsymbol{a}^B + \boldsymbol{g}^B + \boldsymbol{\gamma} \quad (14)$$

where $\boldsymbol{a}_{meas}$ is the measured acceleration, $\boldsymbol{a}^B$ is the sensor acceleration and $\boldsymbol{g}^B$ is the gravity component. The acceleration measured in the sensor coordinate system is transformed into a global coordinate system by use of the estimated orientation of the sensor represented by the rotation matrix $\boldsymbol{R}$. The gravity component can now easily be subtracted as it is constant in the global coordinate system. Equation (14) can now be integrated discretely:

$$T_s \sum_{i=1}^{N} (\boldsymbol{R}(i)\boldsymbol{a}_{meas}(i) - \boldsymbol{g}^I) = \mathbf{v}(N) - \mathbf{v}(1) + T_s \sum_{i=1}^{N} \boldsymbol{R}(i)\boldsymbol{\gamma} \quad (15)$$

The discrete integration goes from 1 to $N$ and $T_s$ represents the step size for the discretisation. $\mathbf{v}(1)$ and $\mathbf{v}(N)$ are the velocities at the beginning and at the end of the swing phase. By applying the restriction that the velocity of the foot is zero at the beginning and at the end of the integration, and by assuming the bias is constant over the integration period, we can calculated the bias $\boldsymbol{\gamma}$ by this equation:

$$\boldsymbol{\gamma} = \left(\sum_{i=1}^{N} \boldsymbol{R}(i)\right)^{-1} \sum_{i=1}^{N} (\boldsymbol{R}(i)\boldsymbol{a}_{meas}(i) - \boldsymbol{g}^I) \quad (16)$$


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The acceleration without the artificial bias can be integrated twice to obtain the position

$$\mathbf{v}^I(i) = \sum_{j=1}^{i} T_s \left[ \boldsymbol{R}(j)(\boldsymbol{a}_{meas}(j) - \boldsymbol{\gamma}) - \boldsymbol{g}^I \right] \quad (17)$$

$$\mathbf{s}^I(i) = \sum_{j=1}^{i} T_s \boldsymbol{v}^I(j) \quad (18)$$

As the heading is not known the step length is calculated from the position in the x and y direction at the end of the integration

$$l_{step} = \sqrt{s_x^I(N)^2 + s_y^I(N)^2}. \quad (19)$$

The foot clearance is defined as the maximum distance in the vertical direction:

$$fc = \max(s_z^I(i)), \ i = 1...N \quad (20)$$

*Gait Phases Detection*

The gait detection algorithm divides the gait cycle in four different gait phases: stance, pre-swing, swing and loading response. These phases can be represented as a state machine with four states similar to the state machine described in the article of Papas et al. [2]. The difference to that paper is the type of sensors applied, with the consequence that the transitions between states are different. The algorithm allows 6 transitions between the states (cf. Figure 5). These are governed by logic functions.

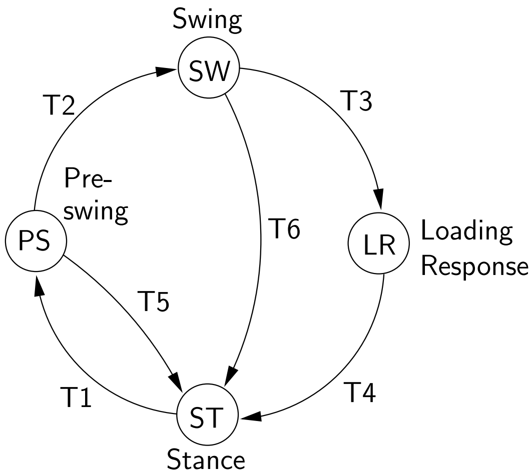


Figure 5: Gait phase detection system represented as a state machine. The gait phases are represented as 4 states where 6 transitions between the states are possible.

Based on the angular velocity measurement a coarse detection is done whether the sensor is at rest or if it is moving. The same detection is also done for robustification using the acceleration measurement. These binary variables are denotes as $x_{a,rest}$ for the accelerometers and $x_{g,rest}$ for the gyroscopes. The logic value one means that the sensor is at rest and zero means that the sensor is moving. The transitions between the states have the following conditions:

*T1: stance → pre-swing*

In the stance phase, the only transition which can occur is to the pre-swing state. This is done when both $x_{a,rest}$ and $x_{g,rest}$ are indicating a movement $(\overline{x_{a,rest}}) \wedge (\overline{x_{g,rest}})$

*T2: pre-swing → swing*

In the pre-swing state the algorithm anticipates the transition to the swing state. The condition for the transition to the swing phase is that at least one of the sensors is not indicating rest, and that the rotation of the foot around the y-axis changes from positive (in the pre-swing state) to negative direction:
$((\overline{x_{a,rest}}) \vee (\overline{x_{g,rest}})) \wedge (\dot{\omega}_y < 0)$.

*T3: swing → loading response*

In the swing phase the algorithm awaits the transition to the loading response phase which begins with the first contact of the foot with the ground. Thus, the algorithm is awaiting for a peak in the accelerometer signals. This is detected when the difference of the acceleration signal in the z - direction is greater than a certain threshold.

*T4: loading response → stance*

After the loading response the next phase is stance which begins when both front and rear part of the foot touch the ground. This event is detected when both the accelerometers and the gyroscopes are indicating rest. The transition condition becomes
$(x_{a,rest}) \wedge (x_{g,rest})$.

*T5: pre-swing → stance*

If the subject lifts the heel and then put it back on the ground, is this event detected as a transition from pre-swing back to stance. This transition is detected when both the accelerometer and the gyroscopes are indicating rest. The transition condition becomes
$(x_{a,rest}) \wedge (x_{g,rest})$.

*T6: swing → stance*

In certain gait pattern the loading response is not detected, as this transition is detected by large peaks in the acceleration. If this is the case, a direct transition from swing to stance is useful. This event is detected when both the accelerometers and the gyroscopes are indicating rest. Further requirements are that the rotational velocity around the y- axis and its derivative are close to zero. The transition condition becomes
$((x_{a,rest}) \wedge (x_{g,rest})) \wedge (\|\dot{\omega}_y\| < \delta_1 \wedge \|\omega_y\| < \delta_2)$.


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*Reference measurement*

In order to evaluate the step length based on the inertial sensors, measurements with a reference system were carried out. The CMS-HS ultrasonic motion analysis system from the company Zebris[1] consists of a transmitter system (3 senders) and markers (microphones). The absolute position is calculated based on the travel time of the signal from each of the 3 senders to the microphone. To synchronise the data an interface was implemented in Matlab/Simulink™. Two separate threads were used to collect data from the CMS-HS and the from the inertial sensor by IFF/HASOMED GmbH respectively. The CMS-HS position data were sampled with a frequency of 25 Hz and the inertial sensors with a frequency of 500 Hz. As the measurements were done on a treadmill, a transformation of the obtained reference position was introduced in order to compare it with the position estimate from the inertial sensor. The following transformation is applied

$$\bar{p}_x = p_x + v_{tm} t \tag{21}$$

where $v_{tm}$ is the treadmill velocity and $p_x$ is the measured position in the walking direction. The step length from the reference measurement was calculated as the difference in the position at the start and the end of a step

$$l_{step,zebris} = \bar{p}_x(t_{stop}) - \bar{p}_x(t_{start}). \tag{22}$$

## Results

Two stroke patients were selected to walk on a treadmill to validate the gait phase detection system as well as the estimation of the step length and foot clearance. Patient 1 was walking with a constant speed of 1.1 km/h and walked 40 steps. Patient 2 was walking with a constant speed of 1.5 km/h and walked 45 steps.

In Figure 6, the detected gait phases for three strides are shown as well as the acceleration for the same time period for one of the patients. The gait detection system was able to detect all phases for all subjects.

| | pre-swing | swing | load-res | stance |
|---|---|---|---|---|
| Mean duration | 0.40s | 0.69s | 0.19 s | 0.74s |
| Standard deviation | 5.00 % | 4.04% | 20.80 % | 8.57 % |

Table 1: Mean value and standard deviation of the duration of the detected gait phases for patient 2

In Table 1 the mean duration and standard deviation of the respectively phases are shown for patient 2. As seen from the table, the duration of the detected phases are quite constant except for the loading response which has a standard deviation of 20 %.

In Figure 7 the foot position is shown. The upper graph shows the position in the walking direction and

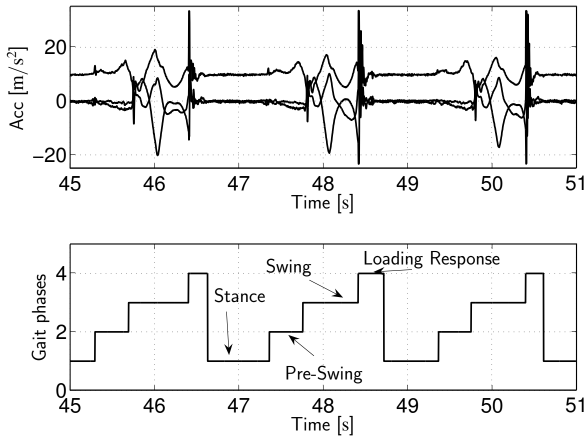


Figure 6: The upper graph shows the measured acceleration. The lower graph indicates the detected gait phases.

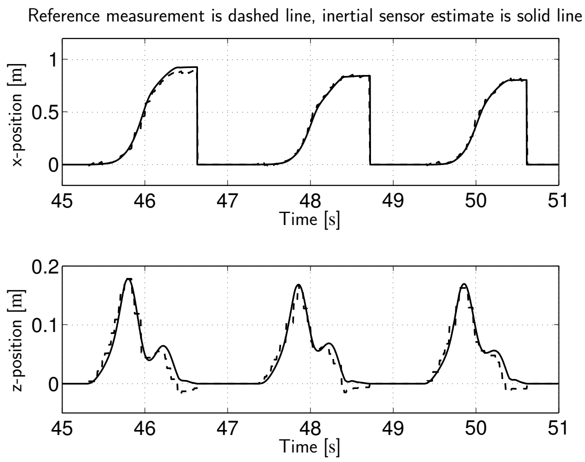


Figure 7: Upper graph shows the position in the walking direction. The lower shows the position in the vertical direction. The dashed line represent the reference system measurement and the solid line the value based on inertial sensor.

the lower graph shows the position in the vertical direction. It can be seen that the estimate of the position is quite accurate and follows the reference system very accurately. The mean values and standard deviations of the error compared with the reference system for both patients are summarised in Table 2, and the step length and foot clearance for some selected steps are compared with the reference measurement in Figure 8. It is observed that the standard deviation of the step length errors lie in the range 1.7 - 3.6 cm which corresponds to 3% -5% of the total length. The mean value of the step length estimation was for all trials larger than the length measured with the reference system.

## Discussion and Conclusions

In the calculation of the foot position, there are several sources of errors. An error in the orientation estimation

[1]Zebris Medical GmbH, Isny, Germany


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| | Patient 1 | Patient 2 |
|---|---|---|
| Mean value of the step length error | 3.63 cm | 1.74 cm |
| Std. deviation of the step length error | 1.65 cm | 3.321 cm |
| Mean value of the foot clearance error | 0.30 cm | 0.50 cm |
| Std. deviation of the foot clearance error | 0.38 cm | 1.30 cm |

Table 2: Mean and standard deviation of the error of the step length estimate

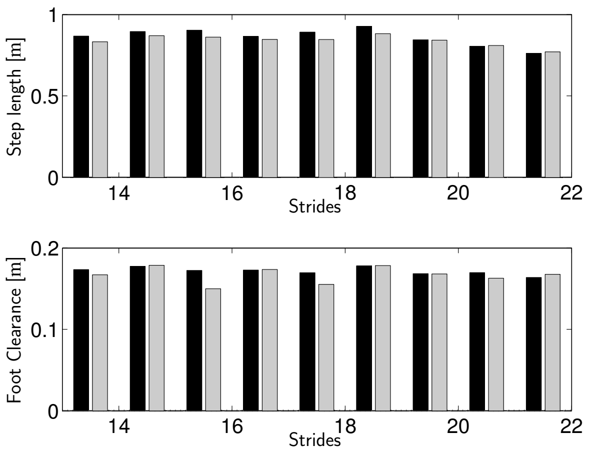


Figure 8: The upper graph shows the step length for 9 steps, the lower graph shows the foot clearance. The dark bars represent the estimated values from the inertial sensor whereas the grey bars represent the reference system measurement.

will of course lead to an error in the acceleration when it is transformed into the global coordinate system. This error can be reduced by applying constrains on the integration. During walking the foot is never completely at rest. This is another source of error because in this case the constraints on the velocity are not valid.

The gait detection system worked robustly for the two patients. The big variance of the duration of the loading response is caused by a large variation of the transition from loading response to stance phase. This transition is based on some threshold values which causes the detection to vary from step to step. Other transitions are more clearly defined events and the duration of the phases dependent on these events can only be explained by natural variation of the gait.

In conclusion, the current study indicates that foot movements and gait phases can be reconstructed from inertial sensor with an accuracy good enough to be used as feedback sensor in FES-aided gait rehabilitation system. The feasibility of such system still has to be demonstrated.

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