Gait Analysis with IMU
Gaining New Orientation Information of the Lower Leg

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Abstract: In this paper we present an application for the analysis and characterisation of gait motion. Using motion data from Inertial Measurement Units (IMUs), seven relevant parameters are measured that extensively charaterize the gait of individuals. Our application uses raw and processed IMU data, where the processed data is the result of filtering the IMU data with a Magdwick filter. The filtered data offers orientation information and is relatively drift free. The IMU data is used to train a three layer neural network that can then extract individual footsteps from an IMU dataset. Results with different test persons show that our application can successfully characterize gait motion on an individual basis and can serve for the clinical assesment and evaluation of abnormal or pathological gait.

1 INTRODUCTION

Even though human gait is quite similar throughout each individual, there are still unique parameters in every single step. These parameters can be investigated to identify an abnormal gait which gives information about the health of the patient. Nowadays gait analysis is often done with optical systems. These systems can deliver highly accurate data, but camera systems can only ”see” patients within a limited field of view. Thus, the use of Inertial Measurement Units (IMU) is advantageous. These sensors are low-cost devices and can be worn all day long, without disturbing the patient’s motion. A considerable amount of literature has been published on gait analysis using IMUs. IMUs have been used to provide data for pedestrian tracking, to reconstruct walking routes, and to analyse the gait of patients with Parkinson’s disease between many other applications. However, most of these applications are affected because IMU measurements tend to drift over time. In 2011 Madgwick *et al.* presented an efficient orientation filter for IMUs (Madgwick et al., 2011). The benefit of this filter is that it can extract the orientation information from the IMU measurements relatively independent of the presence of drifting. In this work, an application is introduced to demonstrate the advantages of the Madgwick filter in terms of gait analysis. An IMU based sensor system was mounted on the lower leg in order to measure its orientation. With this data new gait parameters such as step height, step distance, movement path, hip position and velocity could be obtained.

1.1 Related Work

To date various methods have been developed to measure gait parameters. Gait analysis with IMUs is mainly done by analysing raw accelerometer data (Chung et al., 2012; Sant’Anna et al., 2011; Terada et al., 2011; Gafurov et al., 2007), which provides limited information about the gait. Additionally, this approach requires an accurate orientation of the IMU in *x*-, *y*- and *z*-axis. Otherwise accelerometer data has been used as root mean square, which means a complete loss of orientation information.

Fischer *et al.* describe a method for calculating the route of a passenger using IMUs (Fischer et al., 2012). This method requires the usage of a Kalman Filer to deal with the presence of drift.

Other medical applications of IMU-based gait analysis have been the measurement of movement symmetry in patients with Parkinson disease (Sant’Anna et al., 2011) or Alzheimer’s disease (Chung et al., 2012). There has also been a lot of interest in the area of general movement analysis with IMUs, such as upper body motion tracking (Jung et al., 2010), joint angle measurement (El-Gohary and McNames, 2012) or fall detection for elderly (Wu and Xue, 2008).

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2 METHOD

In this section we present a new approach for gait analysis that uses orientation information provided by data from Inertial Measurement Units (IMUs). The data from the IMUs is first processed using a Madgwick Filter (Madgwick et al., 2011) to produce only the orientation (3D rotation) information of the IMU. The IMU orientation information is fed into a neuronal network to find and characterize individual footsteps in long sets of data obtained from the IMUs. After individual steps are identified in the data sequence, each step is analysed in terms of step length, velocity, lateral amplitude and movement path.

2.1 Position of the IMU

To best identify footsteps in motion tracking data provided by IMUs, there are two possible positions to place the IMU: Foot and lower leg. The position at the lower leg (see fig. 6) offers more robust motion tracking data, since orientation measurements at the foot itself can be distorted as the foot adapts itself to rough terrain while walking. This circumstance can induce errors in the recognition of footsteps, as the foot undergoes slight rotations that are not related to the gait itself when walking over uneven ground. In addition to this, from placement of the IMU on the lower leg we will be able to reconstruct the position and orientation of the lower extremity. For these reasons, our method uses data from IMUs mounted on the lower leg (as shown in figure 6), although this is contrary to the common position of IMUs at the foot, such as found in (Chung et al., 2012; Patterson and Caulfield, 2011).

2.2 Step Recognition

After the IMU data is processed with the Madgwick Filter, we are left with a rotation matrix M_R that gives the 3D orientation of the sensor itself. From the matrix M_R the direction of the sensor coordinate system, with axes x_s, y_s and z_s can easily be determined at any given time. This coordinate system is defined by the rotation of the axes in the global coordinate system (fig. 1), which is determined by the Madgwick Filter, once the sensor unit connects. Accordingly, the angle ω between the lower leg and the direction of gravity can also be calculated, as can be seen in fig. 6. Therefore, the vector corresponding to the direction of the lower leg $\vec{l}$ can be initially assigned on the basis of the sensor axes information while the subject stands still. Assuming that the lower leg is perpendicular to the surface or respectively, parallel to the gravity acceleration while the subject is standing upright, the vector of the lower leg can be determined as the scalar product,

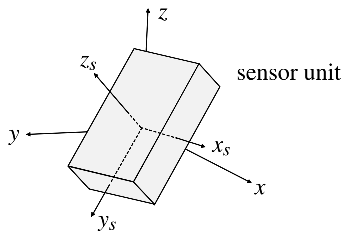

Figure 1: Global coordinate system and sensor coordinate system.

$$l_x = \frac{\vec{x}_s \cdot \vec{z}}{|\vec{x}_s|\,|\vec{z}|}, \quad l_y = \frac{\vec{y}_s \cdot \vec{z}}{|\vec{y}_s|\,|\vec{z}|}, \quad l_z = \frac{\vec{z}_s \cdot \vec{z}}{|\vec{z}_s|\,|\vec{z}|}, \qquad (1)$$

with $z = (0,0,-1)$, the vector of gravity acceleration. The angle ω between $\vec{l}$ and $\vec{z}$ is used for step recognition.

Although there are several pattern recognition techniques that can be used to identify footsteps, we are limited by the fact that footsteps must be characterized individually from subject to subject. For this reason, a three layer feed forward neural network was designed in order to characterize and find steps of different persons in motion tracking datasets. Another possible solution would use supported vector machines, as seen in (Begg et al., 2005) and (Wu, 2012). The recognition of a distinct pattern in a dataset can be seen as a classification problem (Bishop, 2006). In this case there are two possible classes that a dataset can be classified into: contains a footstep and does not contain a footstep. Since a dataset is obtained by recording a subject's gait over several minutes, there are many footsteps to be found in the post processing. In order to find each step, the dataset is divided into sequences of 200 samples each, which represent two seconds of motion with a sampling frequency of 100 Hz. If no step is found inside a sequence k in the database (where k is the position of the first sequence sample in the dataset), a new sequence is taken starting at sample $k+10$, as can be seen in figure 2.

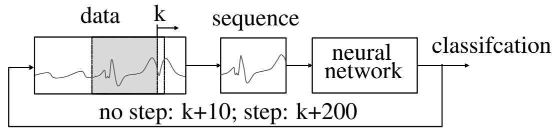

Figure 2: Step recognition using a sequence of 200 data points inside a long dataset.

In the case that a footstep is identified in the 200 sample sequence k, the next sequence to be input to the neural network starts at sample $k+200$. Sequences are input into the neural network, until the end of the dataset is reached. Features are extracted from each sequence in order to fasten the learning process of the neural network. To extract features from a sequence, we find all the extrema of $\omega(t)$ and calculate specific parameters such as distance between maxima or the gradient of certain sections. An overview of the feature extraction can be seen in fig. 3. If the feature being learned is a continuous one,

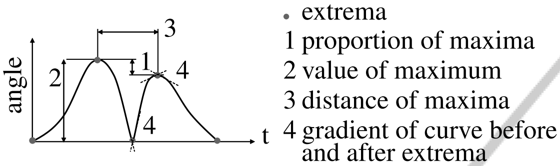

Figure 3: Overview of the most important features that are extracted from a sequence.

like a gradient or a distance, the firing neurons are dependent on the continuous input value. For example, when the feature that we want to characterize (we want the neural network to learn) is a gradient m_x of a section before a minimal turning point, the firing neurons could be defined as:

$$
\begin{aligned}
\mathrm{N[n]} &= 1 \quad \text{if: } m_x < 1 \\
\mathrm{N[n+1]} &= 1 \quad \text{if: } 1 < m_x < 2 \\
\mathrm{N[n+2]} &= 1 \quad \text{if: } 2 < m_x < 3 \\
&\vdots \\
\mathrm{N[n+9]} &= 1 \quad \text{if: } m_x > 10
\end{aligned}
$$

As can be seen, continuous features of the curve, such as proportion of maximal turning points or gradient before minimal turning points, are assigned to an amount of 8-10 input neurons, although the number of input neurons adapt to the variability of the continuous signal. Finally all features together lead up to 110 input neurons. The hidden layer of the neural network improves the recognition of patterns if classes need to be separated multidimensionally. The hidden layer in this application consists of 10 neurons, with the sigmodial activation function:

$$f_{act}(net) = \frac{1}{1+e^{-net}} \tag{2}$$

With the addition of a threshold of 1, the resulting neural network can be seen in fig. 4. The learning rate of the neural network is the factor that influences the convergence of the learned features. It is set to 0.1, as advised in (Bishop, 2006). Using the described feature extraction process, only a small number of input data was required to train the network. After 50 patterns of various footsteps were presented to the network, footsteps in an arbitrary dataset were found

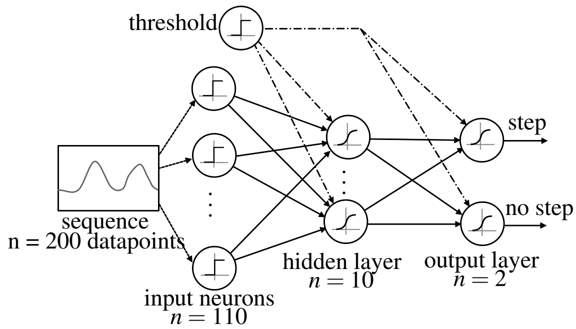

Figure 4: Neural network with three layers.

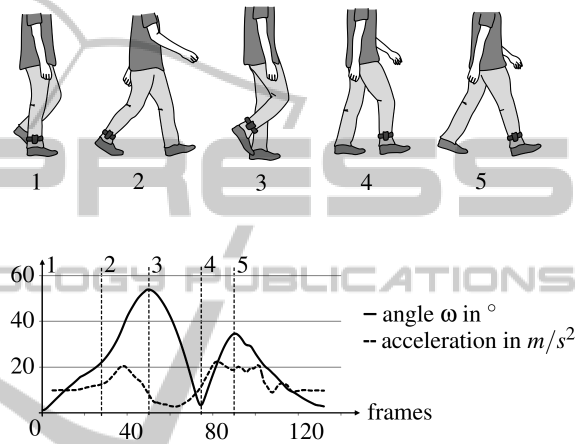

Figure 5: Angle of the lower leg to z-axis and root means square of acceleration data during a step.

with an exactness of 94%. Each learning sequence that was used to train the network was trimmed, so that it represented a motion sequence as seen in fig. 5.

2.3 Step Parameter Calculation

It is possible to extract various features of a step using the orientation information from the IMUs. In the following, the x- and y-axes are located in the transversal plane (corresponding to the floor plane) and the z-axis is defined in the direction of gravity, perpendicular to $\vec{x}$ and $\vec{y}$. x, y and z-axes are defined as the global coordination system, and x_s, y_s and z_s-axes are the sensor axes, see fig. 1.

2.3.1 Direction

The direction of a step, which we define as the provisional movement direction vector $\vec{d}_*$, can be determined by projecting the vector of the lower leg $\vec{l}$ to the x/y-plane (fig. 7) The angle θ inside the x/y-plane can be determined as:

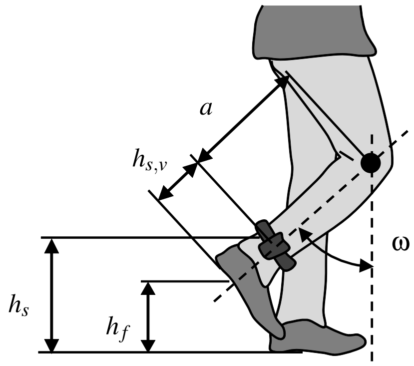

Figure 6: Parameters of foot height computation at a specific time.

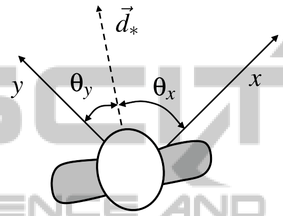

Figure 7: Top view of the vectors for receiving movement direction. The orientation of the global coordinate system x and y-axes is defined by the Madgwick Filter as explained above.

$$\theta_x = \arccos\left(\frac{\vec{x}\cdot\vec{d}_*}{|\vec{x}|\,|\vec{d}_*|}\right) \quad \text{and} \quad \theta_y = \arccos\left(\frac{\vec{y}\cdot\vec{d}_*}{|\vec{y}|\,|\vec{d}_*|}\right) \tag{3}$$

Since there are four quadrants in the x/y plane, a distinction of cases needs to be done in order to find the correct angle of movement direction θ:

$$\theta = \begin{cases} \theta = \theta_x & \text{if } \theta_x < 90^\circ \text{ and } \theta_y < 90^\circ \\ \theta = \theta_x & \text{if } \theta_x > 90^\circ \text{ and } \theta_y < 90^\circ \\ \theta = \theta_y + 90^\circ & \text{if } \theta_x > 90^\circ \text{ and } \theta_y > 90^\circ \\ \theta = 360^\circ - \theta_x & \text{if } \theta_x < 90^\circ \text{ and } \theta_y > 90^\circ \end{cases} \tag{4}$$

With θ already known, the vector of movement direction $\vec{d}$ can be calculated as,

$$\vec{d} = \begin{pmatrix} \cos\theta \\ \sin\theta \\ 0 \end{pmatrix} \tag{5}$$

2.3.2 Step Length

The vertical position of the sensor $s_r(t)$ at a given time t during a step is the double integration of the acceleration $a_d(t)$, in the direction of movement. Accordingly the final step length s_r is the position of the foot at the end of the step. The acceleration data in x_s, y_s and z_s-direction is directly obtained from the IMU. The acceleration in the direction of movement a_d can simply be maintained by calculating the dot product of the x_s and y_s axes with $\vec{d}$. Afterwards these two ratios are each multiplied with the measured acceleration a_x respectively a_y. Therefore, the step length $s_r(t)$ is:

$$s_r(t) = \left(\int_0^t \int_0^t a_d(t)\,\mathrm{d}t\,\mathrm{d}t\right) \tag{6}$$

2.3.3 Route

The route can simply be maintained by multiplying the direction vector $\vec{d}$ with the final step length s_r. The route is built as a sequence of points representing the history of the motion direction in the x/y plane. A new route point $P_{n+1}(x,y)$ in x and y-direction is calculated as:

$$P_{n+1}(x) = P_n(x) + \vec{d}_x s_r \qquad P_{n+1}(y) = P_n(y) + \vec{d}_y s_r \tag{7}$$

2.3.4 Step Height

The vertical position of the sensor $h_s(t)$ during a step can be obtained by double integration of the acceleration $a_z(t)$ in the z direction:

$$h_s(t) = \int_0^t \int_0^t a_z(t)\,\mathrm{d}t\,\mathrm{d}t \tag{8}$$

Since the sensor is placed on the lower leg and not on the foot itself, the vertical position of the foot $h_f(t)$ cannot be measured directly. First, the vertical position of the sensor needs to be calculated. With l_L the known length of the lower leg, and $\omega(t_*)$ the angle between lower leg and the z-axis, the distance a of the sensor to the knee (center of lower leg rotation) is:

$$a = \sqrt{\left(\frac{h_s(t_*)}{\cos\left(-\frac{1}{2}\omega(t_*)\right)}\right)^2 \frac{1}{2(1-\cos(-\frac{1}{2}\omega(t_*)))}} \tag{9}$$

In this case, a is calculated at a specific time (t_*), where the angle $\omega(t)$ is maximal. Therefore the height of the sensor $h_{s,v}$ from the sole of the foot can be obtained with:

$$h_{s,v} = l_L - a; \tag{10}$$

Now the height of the foot $h_f(t)$ over time can be obtained with:

$$h_f(t) = (h_{s,v} + h_s(t)) - cos(\omega)h_{s,v} \tag{11}$$

This means that the position of the sensor (a couple of centimeters higher or lower) can vary and we will still be able to get a correct measurement of $h_f(t)$. An overview of the calculated parameters can be seen in fig. 6.

2.3.5 Foot Position in Movement Direction

Analogous to the height h_f of the foot, the position s_f of the foot can be calculated. In order to get s_f a distinction of cases with respect to the angle ω must be taken into account. ω is defined negative if the foot position is posterior and positive if the foot position is anterior.

$$s_f(t) \begin{cases} s_r(t) - \sin(|\omega|)h_{s,v} & \text{for } \omega < 0 \\ s_r(t) + \sin(|\omega|)h_{s,v} & \text{for } \omega > 0 \end{cases} \quad (12)$$

2.3.6 Lateral Amplitude

The lateral amplitude $s_l(t)$ can be defined as the angle of the foot to the plane parallel to the direction of movement. That means, the dot product between the direction of movement $\vec{r}$ and the gravitation vector $\vec{z}$ needs to be calculated, in order to obtain the normal vector $\vec{n_d}$ of the plane parallel to the direction of movement.

$$\vec{n_d} = \vec{r} \times \vec{z} \quad (13)$$

Afterwards the angle between the lower leg vector $\vec{l}$ and $\vec{n_d}$ can be easily computed as seen in (3). This angle is the lateral amplitude, which indicates if a patient has limping gait or not.

2.3.7 Position of Thigh

With the vertical foot position $s_f(t)$, the horizontal foot position $h_f(t)$ and the angle $\omega(t)$ at any given time, the gait can be visualized. But since there is only one sensor placed on the lower leg, the position of the thigh needs to be predicted. Using the results of gait analysis (Perry, 2003) a best-fit curve of the angle $\gamma(p)$ between the lower leg vector $vec(l)$ and the thigh is determined. The angle $\gamma(p)$ is determined with respect to the step phase p (expressed as a percentage).

$$\gamma(p) = \begin{cases} 175° & \text{for } p < 20\% \\ f(p) & \text{for } 20\% < p < 75\% \\ 175° & \text{for } p > 75\% \end{cases} \quad (14)$$

with $f(p)$ a polynomial of the 5th order:

$$f(p) = 4.1 \cdot 10^{-6} p^5 - 9.8 \cdot 10^{-3} p^4 + 0.1p^3 - 3.4p^2 + 56.3p - 153.4 \quad (15)$$

Thereby the position of the thigh (and hip) can be reasonably approximated. Some of the calculated parameters can be seen in fig. 8. As can be seen, the angle $\omega(t)$ and the lateral amplitude over time give additional information about the gait.

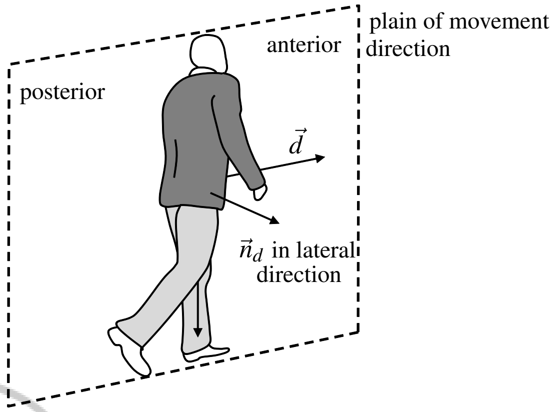

Figure 8: Gait parameters. The lateral amplitude is defined as the angle between the lower leg and z-axis in direction of $\vec{n}_d$.

3 RESULTS

The proposed methodology allows a near complete characterization of the different gait parameters. For instance one single step of a 25 year old male subject results in the following parameters:

step length:	1.38 m
max. posterior amplitude (fig. 5 (3)):	43°
max. anterior amplitude (fig. 5 (5))	40°
max step height h_s:	24 cm
step duration:	1.17 s
average velocity:	1.18 m/s

The corresponding graph of one single step can be seen in fig. 9.

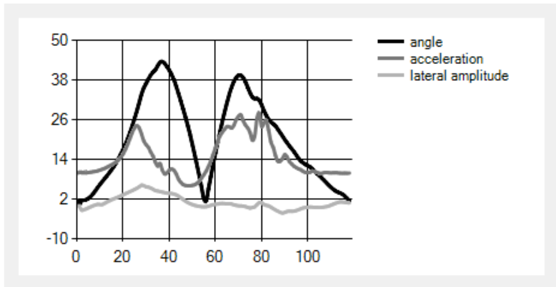

Figure 9: Step analysis. The developed application computes step length, step duration, max. lateral amplitude and average velocity. Furthermore a graphical output gives information about the angle $\omega(t)$, acceleration (rms) and lateral amplitude over time.

To validate the algorithms three subjects were requested to walk ten steps along a straight line. The sensor was placed on the left lower leg. Afterwards the distance was measured and the results were compared using the computed step length of a whole step

Table 1.

subject	distance	calculated	difference
1	13.70 m	14.10 m	2.9%
2	13.30 m	13.96 m	4.9%
3	12.90 m	13.38 m	3.7%

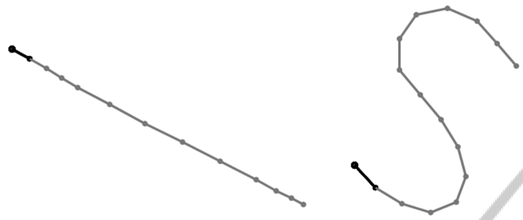

Figure 10: Movement paths, top view. *left*: walking over a straight line with different step length. *right*: walking an s-shape trajectory. The black line marks the beginning. Each step ends with a dot, so that different step lengths can be seen.

s_r. As can be seen in Table 1, there is an average error of 3.8% percent between the actual walked distance and the calculated distance. That is about 4 cm of error measurement at every step.

Additionally sensor orientation is used to detect the direction of movement. One subject was requested to walk in a straight line with small steps at the beginning, normal step size in the middle and small steps at the end. As can be seen in fig. 10 the route and the variability in step length can easily be determined. The developed algorithm works with non-linear walking routes as well, as can be seen to the right of fig. 10. For this figure, the subject was asked to walk an s-shape trajectory with normal step size. The walking route was determined using the algorithm presented here.

4 CONCLUSIONS

Using raw IMU information and IMU information filtered with a Madgwick filter we were able to outline a new application to extensively characterize gait parameters that provide new information about leg orientation and movement direction.

In the future we suggest more studies to outline the limitations of the developed application. The algorithm for gait analysis needs to be tested with various pathological patients and with the results of such tests, there will be a possibility to automatise long-term gait analysis. With that in mind, patients suffering from conditions whose severity can be at least partially assessed by continuous gait analysis can profit from the monitoring application presented in this paper.

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