Estimation of gait parameters based on data from inertial measurement units

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***Abstract*— We developed a method based on an artificial neural network for the estimation of gait parameters from data recorded by inertial measurement units (IMU) mounted on the shank and foot. The input for the training of the neural network are the signals recorded by inertial measurement units (Yost Labs, Portsmouth, Ohio, USA) positioned at the foot and the shank, and the output of the network are the fuzzified data from the sensors recorded by the force transducers built into the insoles. The communication between the sensors and the computer was realized wirelessly. The input and output data were captured synchronously on a Windows platform during the gait. The differences between the gait parameters (relative errors) estimated from the reference data and the IMU system were below 4%. The system is now being used in a small clinical trial in stroke patients.**

***Index Terms*— gait cycle, gyroscope, ground reaction force, neural network**

I. Introduction

The assessment of the gait in the rehabilitation uses semi-subjective heuristic description based on the expertise and experience of a clinician. Current instrumentation (camera based systems recording the markers mounted on the body and force platforms measuring the ground reaction force [1-2], instrumented walkways [3-5], wearable systems composed of inertial measurement units and instrumented insoles [6-8], and instrumentation for measuring electromyography) allows the quantification of gait [9-10]. The quantification is based on the data characterizing mechanics (joint angles [11], ground reaction forces [12], joint forces and torques [13], angular velocities and accelerations [14-15], power, energy) or physiological activity that is responsible for the gait (electromyography – EMG) [16-18]. The quantification can also combine the mechanical and physiological measures. For clinical applications, the complex data can be reduced to a set of scalar measures describing the most relevant parameters (events defining the gait). This study is directly related to the estimation of the following gait parameters:

- stride cycle – time between the two consecutive heel contact (HC) of the same leg;
- step cycle – time between the HC of the ipsilateral leg and the HC of the contralateral leg;
- stance phase – time between the HC and the toes off (TO) of one leg;
- swing phase – time between TO and HC of one leg;
- single support phase (SSP) – time when only one leg is contacting the ground;
- double support phase (DSP) – time when both legs are contacting the ground;
- gait cadence – number of steps per unit time.

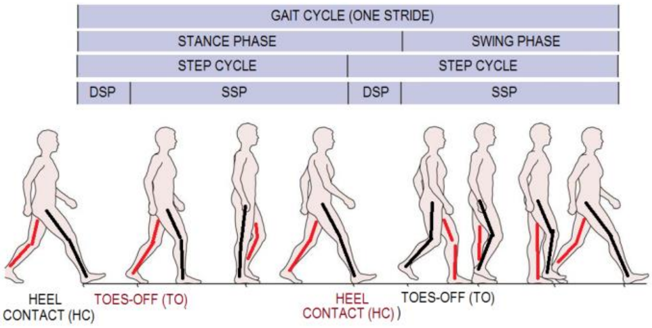

Fig. 1: Gait phases defining the parameters of interest.

The simplest method for determining the listed gait parameters are walkways and instrumented insoles. The walkway limits the gait to a fixed geometry [3-5], and the insoles are not robust sufficiently for the prolonged free gait. The limitations were the motivation for testing and validating the use of a simple wearable system with only two inertial measurement units (IMU) for the estimation of gait parameters in the clinical environment. We compared the results obtained by IMUs with results obtained by instrumented insoles, as a referent system. To accomplish the task we developed a computer simulation based on an artificial neural network which uses data from inertial measurement units as inputs and fuzzified ground reaction force signals from instrumented insoles as the output (reference data).

We present the method and the comparison of the gait parameters determined by both systems.

II. Methods

A. Instrumentation

We used the custom designed system Walky® (Fig. 2) for the measurements. The system comprises two insoles (five sensors in each insole) and four IMUs (Yost Labs, Portsmouth, Ohio, USA https://yostlabs.com) measuring

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angular rates (3-axis gyroscope) and accelerations (3-axis accelerometer). The size of insoles can be set to fit the foot size. Walky system sends wirelessly signals as 100 Hz sampling rate to the host PC.

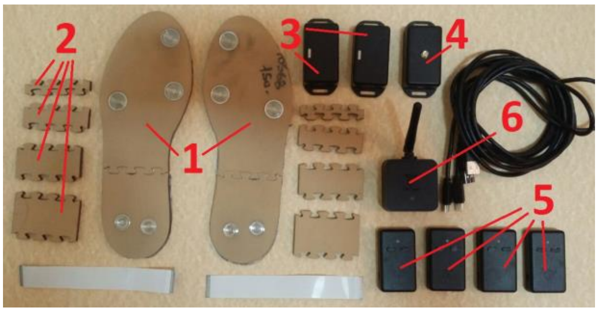

Fig. 2. Walky system: two insoles with five force transducers each (1), extensions for insoles (2), wireless emitters (3) for sensors in insoles which communicate with a computer by a dongle (4), four IMUs (5) which communicate wirelessly with a dongle (6).

B. Subjects and Procedure

We recorded data from five healthy subjects (three male and two female, 26±4 years old).We attached two IMUs per leg: one unit was placed on the top side of the foot and the second on the proximal side of the shank below the knee (Fig. 3). Before the placing insoles, we set offset of force sensors to zero. We also set the size of insoles to match the size of subject’s foot. After attaching all sensors to the appropriate positions, the subject was asked to walk in straight line for about ten standard steps. The gait always started from the standing with both feet on the ground.

Figure 3. The sketch of the positions of IMU sensors.

C. Signal processing

Signals were processed offline in Matlab R2015a (The MathWorks, Natick, MA, USA). We applied Butterworth low-pass filter (5^{th} order, the cutoff frequency of 3Hz) on angular velocity signals to reduce noise and the impact artifacts during the heel contact. All signals were normalized by dividing all signals recorded by one recording unit with maximal absolute value recorded with that IMU. This normalization set the range for the force signals to [0, 1] and the angular velocity signals to [-1, 1].

We used fuzzy logic to estimate the phases of gait cycle from the foot pressure signals. Inputs for the fuzzy logic were three signals: heel force, metatarsal force and toes force. We set two spline-based membership functions for each input:

$$f_1(x;a,b) = \begin{cases} 0, & x \le a \\ 2\left(\frac{x-b}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-a}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 1, & x \ge b \end{cases}$$

$$f_2(x;c,d) = \begin{cases} 1, & x \le c \\ 1-2\left(\frac{x-c}{d-c}\right)^2, & c \le x \le \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \le x \le d \\ 0, & x \ge d \end{cases}$$

where x is the time sample of the signal, and a, b, c and d the parameters of curves given in Table 1.

TABLE 1. PARAMETERS OF MEMBERSHIP FUNCTIONS

	a	*b*	*c*	*d*
heel	0	0.1	0.005	0.025
metatarsal	0	0.1	0.005	0.025
toes	0	0.02	0	0.02

We used additional rules for the fuzzification shown in Fig. 4. The output of the fuzzy logic has four values for four phases: swing, heel contact, flatfoot, and heel off (Fig. 4).

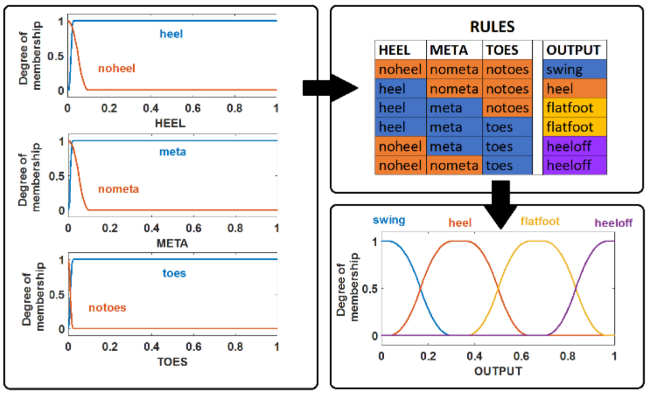

Fig. 4. Illustration of the fuzzification for the estimation of the gait phases from foot pressure sensors. It has three inputs, each with two slope-based membership functions (left panel), additional rules (top right panel) and one output with four values for four phases: swing, heel, flatfoot and heel-off (bottom left panel).

To estimate the gait phases from IMU signals, we used an artificial neural network (ANN). To minimize the error of phase recognition, we used cascade method based on two neural networks (Fig. 5). First ANN divides the signal into swing and stance phase. Second ANN recognizes flat foot phase in stance phase. Heel-on phase is obtained as the time between the beginning of the stance phase and the beginning of the flat foot phase. Similarly, the heel-off phase is obtained as a time between the end of the flat foot phase and the end of the stance phase. We divided swing phase into acceleration phase and deceleration phase by finding a local maximum in part of the intensity of the angular velocity signal during the swing phase. The intensity of the angular velocity is obtained as the root of the sum of squared component signals.

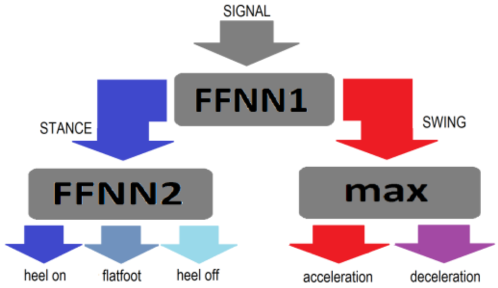

Fig. 5. Algorithm for detection of gait phases based on two cascaded neural networks: FFNN1 separates the swing and stance phases, and FFNN2 detects subphases of the stance phase: heel-on, flat foot, and heel-off. Swing phase is divided into acceleration and deceleration phases by the estimation of the maximum value of the angular velocity in the swing phase.

The ANN used are feedforward neural networks with ten inputs and ten outputs with linear transfer functions, and three hidden layers with sigmoidal transfer functions. The first ANN has 25 neurons in the first layer, 12 in the second and 7 in the third layer (Fig. 6, top panel). The second ANN has 25 neurons in the first layer, 13 in the second and 7 in the third layer (Fig. 6, bottom panel). The number of layers and neurons was determined heuristically. The inputs for neural networks are sets of 10 adjacent samples of gyroscope signal from sagittal plane. We made window ten samples wide to go through the signal to collect samples for the neural network. The outputs for the first ANN are the sets of binary values corresponding to swing (value 1) and stance (value 0) phases, obtained from the fuzzy logic described before. Similarly, the outputs for the second ANN are the sets of binary values corresponding to flatfoot (value 1) and all other (value 0) phases. Our training data set contained 500 x 10 data samples from all five subjects. We used 70% of data for training 15% for testing, and 15% for validation. We used Matlab Neural Network Toolbox, to obtain ANNs.

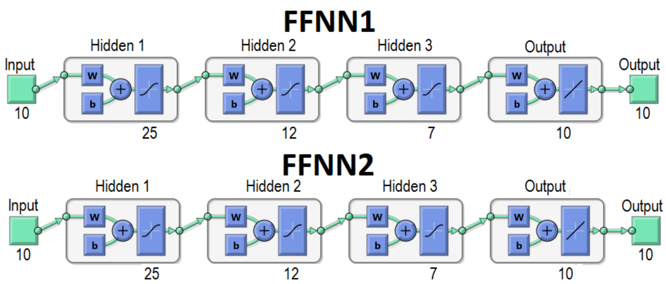

Fig. 6. FFNN1 is a feed-forward ANN for separation to the swing and stance phases and FFNN2 a feed-forward ANN for the detection of subphases of the stance phase.

III. Results

Fig. 7 shows recorded signals for subject Nº 1 for nine steps (5 with left and 4 with right leg). Top panels show signals from insole sensors and middle and bottom panels show signals recorded by IMU sensor placed on feet and shanks.

In Fig. 7 we can notice the repetitive pattern of the gait cycle. The heel contact is at the time when the heel contact signal starts rising, while other two signals are zero. At the same time, the angular velocity measured by IMU increases from negative local minimum to zero. When the whole sole contacts the ground (all three insole sensors above the threshold), then the flat foot occurs. The flat foot beginning coincides with the rise of the signal from the metatarsal zone sensor. The angular velocity of the foot during the flat foot phase is zero because foot does not move. When the signal from the sensor under the heel falls to below the threshold, then the heel off phase starts. During this phase, angular velocity declines because foot and shank are leaning in front of the vertical line. The swing phase begins at push off moment, which can be detected when the signal from the sensor under the toes falls to zero. During the swing phase, angular velocity rises from local minimum (acceleration phase) to highest peak in whole gait cycle which correspond to mid-swing. At that moment leg is fully extended, and heel starts to move toward the ground (deceleration phase).

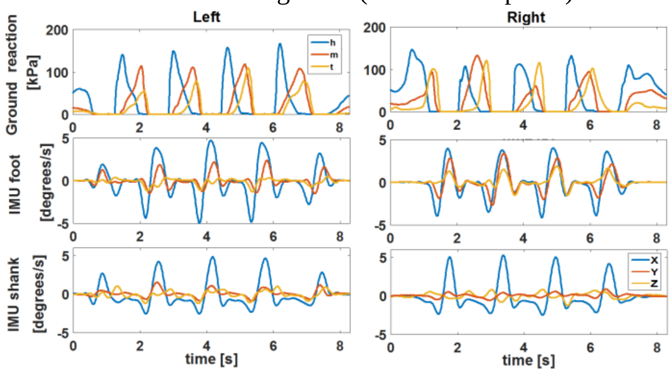

Fig. 7. Recorded signals for subject Nº1 for nine steps (5 with left and 4 with right leg). Top panels show signals from foot pressure sensors (heel – blue; metatarsal – orange; toes - yellow), and middle and bottom panels show signals recorded by IMU placed on feet and shanks (X-axis – blue; Y-axis – orange; Z-axis - yellow).

Fig. 8 shows confusion matrices for the trained ANN. FFNN1 has two output classes: 0 (stance phase) and 1 (swing phase), and the FNN2 has two output classes: 0 (heel on or heel off phase) and 1 (flat foot phase). The mean square errors for the FFNN1 are 2.2% and for the FFNN2 are 6.8%.

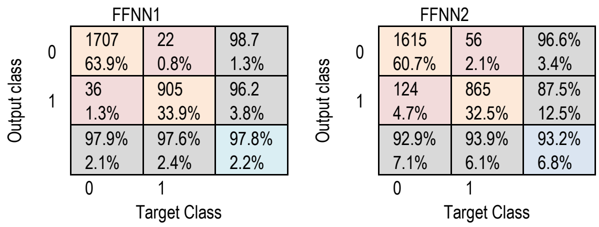

Fig. 8. Confusion matrices for the trained neural networks. First neural network (FFNN1, left) has two output classes: 0 (stance phase) and 1 (swing phase). Second neural network (FFNN2, right) has two output classes: 0 (heel on or heel off phase) and 1 (flat foot phase).

Fig. 9 shows the comparison of signals and detected gait phases, recorded by force sensors (top panel) and signals (angular velocities) recorded by the IMU gyroscope (middle and bottom panels) which was placed on the foot. The data shown are from the sensors on the left leg of subject Nº 1.

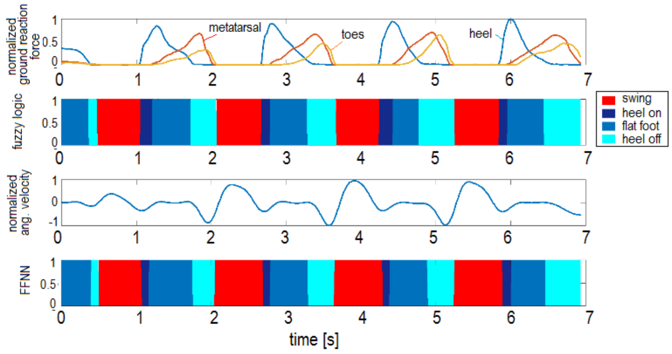

Fig. 9. Comparison of signals and detected gait phases, recorded by foot pressure sensors (top panels) and signals recorded by gyroscope placed on foot (bottom panels) on the left leg of subject 1.

Fig. 10 shows the comparison of gyroscope signals and detected gait phases on both legs for subject Nº 2.

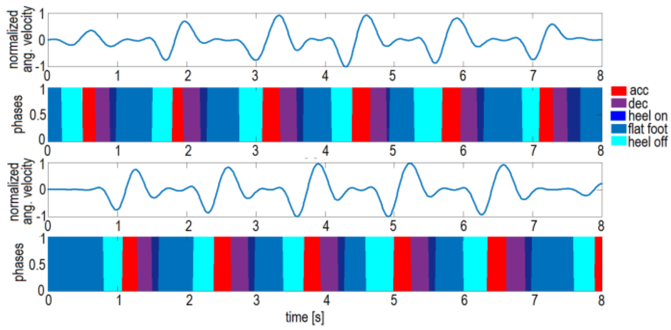

Fig. 10. Comparison of signals and detected gait phases on both legs for subject Nº 2.

Table 2. shows the errors estimated for the duration of phases detected from gyroscopes and the phases detected from ground reaction force for all subjects.

TABLE 2. ERRORS (IN %) OF ESTIMATED LENGTH OF PHASES DETECTED FROM GYROSCOPES AND GROUND REACTION FORCE SENSORS FOR ALL SUBJECTS.

Subject	*SWING*	*Heel on*	*Flat foot*	*Hell off*
Nº 1	1.64	11.11	8.33	2.33
Nº 2	2.44	12.1	8.87	3.1
Nº 3	3.28	11.3	8.82	3.4
Nº 4	0.05	10.5	7.9	2.21
Nº 5	1.54	11.3	8.22	2.42

Table 3. shows gait parameters obtained from ground reaction force signals for all subjects.

TABLE 3. GAIT PARAMETERS OBTAINED FROM GROUND REACTION FORCE SIGNALS FOR ALL SUBJECTS.

Subject	*Step [s]*	*Stride [s]*	*Stance [s]*	*Swing [s]*	*SSP [s]*	*DSP [s]*	*Cadence [steps/min]*
No 1	0.8	1.6	0.98	0.61	0.37	0.19	87
No 2	0.65	1.27	0.76	0.41	0.33	0.14	105
No 3	0.83	1.67	1.06	0.61	0.35	0.23	84
No 4	0.73	1.45	0.88	0.56	0.34	0.18	98
No 5	0.73	1.52	0.87	0.65	0.38	0.14	95

Table 4. shows gait parameters obtained from IMU sensor placed on foot for all subjects.

TABLE 4. GAIT PARAMETERS OBTAINED FROM IMU SENSOR PLACED ON FOOT FOR ALL SUBJECTS

Subject	*Step [s]*	*Stride [s]*	*Stance [s]*	*Swing [s]*	*SSP [s]*	*DSP [s]*	*Cadence [steps/min]*
Nº 1	0.8	1.58	0.96	0.62	0.34	0.2	87.5
Nº 2	0.65	1.2	0.77	0.42	0.32	0.15	105
Nº 3	0.83	1.68	1.08	0.59	0.34	0.23	83.8
Nº 4	0.72	1.43	0.86	0.56	0.34	0.16	97.6
Nº 5	0.73	1.53	0.89	0.64	0.36	0.13	95.02

Table 5. shows gait parameters obtained from IMU sensor placed on shank for all subjects.

TABLE 5. GAIT PARAMETERS OBTAINED FROM IMU SENSOR PLACED ON SHANK FOR ALL SUBJECTS.

Subject	*Step [s]*	*Stride [s]*	*Stance [s]*	*Swing [s]*	*SSP [s]*	*DSP [s]*	*Cadence [st/min]*
Nº 1	0.8	1.6	1.01	0.59	0.35	0.22	90
Nº 2	0.66	1.31	0.81	0.4	0.31	0.17	107.2
Nº 3	0.84	1.66	1.13	0.56	0.33	0.27	83.3
Nº 4	0.71	1.49	0.93	0.56	0.35	0.16	97.22
Nº 5	0.73	1.55	0.9	0.65	0.39	0.17	96

TABLE 6. ERRORS OF ESTIMATED GAIT PARAMETERS (IN PERCENT).

Subject	*Nº 1*	*Nº 2*	*Nº 3*	*Nº 4*	*Nº 5*	*All*
			Foot			
[%]	1.9	2.78	1	2.85	1.99	2.1
			Shank			
[%]	4.17	4.96	5.8	4.62	3.26	4.56

The errors of estimation of the gait parameters are presented in Table 2.

IV. DISCUSSION

In the top panel in Fig. 9 we can notice that the swing phase is not divided into the acceleration and the deceleration phase. During the swing phase, the ground reaction force is zero, because the foot is not touching the ground. To find the mid-swing we selected to find the maximum value of the angular velocity during the swing phase.

The confusion matrices in Fig. 8 show that NNs have been trained well based on the calculated small mean square errors. These errors manifest as gaps in phases. These gaps are easy to correct afterward, by merging them with surrounding phase by using the constraint that the phase will be considered only if it lasts for a minimum of 100 ms. If we used only one ANN to detect all phases, then the correction of these errors would be much more complicated.

We calculated all gait parameters based on heel contact and toes off moments. Therefore, only the detection of swing and stance phase has the influence to the accuracy of these parameters. As we can notice in Table 6, the error of estimation of gait parameters from angular velocity of the foot is 2.1 % that fits the error of FFNN1, which is used as the decision for the differentiation between the swing and the stance phases. When we applied same NN to the signals from IMU placed on the shank, the error increased to 4.56%. This increasing error was expected because the angular velocity of the shank carries less information about the phase of the gait compared with the information from the foot. To improve accuracy and have a more robust system we should train NN with more samples coming from sensors positions at different places on the shank and foot.

In Table 2 we can notice that errors of estimation of sub-phases of the stance phase are significantly larger than errors of estimation of swing phase and stance phase. The duration of these sub-phases is approximately three times shorter than swing phase. Therefore, one or two wrongly classified samples have a large influence to the error. This result was expected because in the swing phase and the heel off phase there is much more movement of a foot than in other phases. Therefore, from the heel contact to the beginning of the heel off phase there, there is a relatively small variation of angular velocity signal, and it hinders accurate classification. Since determining of the beginning of flat foot phase is not an important parameter for the gait analysis, IMUs still can provide acceptable results for the clinical work.

The primary goal of this study was to evaluate the simple system consisting of IMU positioned at the leg for detection of gait phases. We show that this was a valid hypothesis. Literature data [10-12] report the mean errors in the range between 2.7% and 12%; hence, our results prove that the suggested instrumentation and signal processing are applicable for clinical gait analysis in rehabilitation.

To improve the accuracy presented in this manuscript a larger dataset should be used for the training of the neural network, and short time series of consecutive moments used instead of only one moment like it was done in [16]. The further tests need to include various gait modalities.

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