A Gait Phase Detection System based on Peak Detection Method and Neural Network

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Abstract

Accurate human gait phase detection is imperative in rehabilitation and robotics, forming the foundation for developing adaptive technologies and interventions. Precise gait detection enables the timing and coordination of robotic assistance or rehabilitation exercises tailored to specific gait cycle phases. In this study, a custom designed inertial measurement unit was fixated on an individual's lower back, and a peak detection method was developed for detecting heel strike and toe-off events. The method solely uses the linear acceleration data along the subject's walking direction. Two insoles with push button switches were placed in the subject's custom-designed shoes to identify instants of foot contact and lift-off. The differences between the timing and peak linear accelerations of the switches were measured. Subsequently, distinct phases of gait on the right and left feet were detected, and data labeling was performed. This process was repeated for 14 trials, generating a dataset comprising the linear acceleration and angular orientation. Finally, a neural network model was designed, trained, and evaluated using this dataset. The proposed technique demonstrated a notable performance in detecting the defined phases with approximately 85% accuracy on average for all phases.

Keywords: Gait Phase Detection, Inertial Measurement Unit, Instrumented Insole, Neural Network

Introduction

Detection of human gait phases is crucial in advancing research on musculoskeletal biomechanics [1], rehabilitation [2-4], and development of assistive devices [5]. It also provides important information for generating appropriate torque and force to assist the patients' walking in exoskeleton robots [6-8]. By tracking and precisely analyzing the walking stages, researchers and physicians can gain insights into movement patterns [9], identify the abnormalities [10], and conduct suitable interventions to enhance the mobility and overall walking performance [11].

Various tools including the image-based optical motion capture systems and wearable devices equipped by force sensing resistor (FSR) sensors, electromyography (EMG) sensors, and inertial measurement units (IMU) are widely used for walking phase detection. Among these equipments, IMUs offer a more flexible and cost-effective solutionwith an increasing demand for use as a tool for detecting and measuring various parameters in walking analysis. Several techniques have been introduced for detecting walking phases using an IMU. Zhao et al. [11] applied the time-frequency analysis method on the acceleration signals measured by two IMUs placed on the ankle. With the help of Vicon motion capture system, they could develop a rule-based algorithm for detecting the Swing and Stance phases. In another study, Yan et al. [12] used the acceleration data measured by three IMUs on ankle, shin, and thigh in order to identify these phases by using a neural network trained based on the labeled data derived from phase segmentation percentages [13]. Binbin Su et al. [14] developed a convolutional neural network to detect five phases including the loading response, mid-stance, terminal stance, pre-swing, and swing. They trained the network using linear acceleration, angular velocity, and magnetic field data measured by seven IMUs, along with labels obtained from the insole switch. Based on data from a single IMU placed on the ankle Pérez-Ibarra et al. [15] proposed an adaptive thresholding algorithm using genetic algorithm to detect phases of Heel-Off (HO), Toe-Off (TO), Heel-Strike (HS), and Toe-Strike (TS). They used the labeled data obtained from videos of the individual during walking. Miguel et al. [16] labeled four phases (Swing, Foot Flat, HO and HS) using FSR insoles based on linear acceleration and angular velocity data from an IMU placed on foot. To detect these phases, they proposed two algorithms: a threshold-based algorithm and a hidden Markov model utilizing IMU data. Zakria et al. [17] introduced a sophisticated rule-based algorithm for identifying four distinct phases (Initial contact (IC), TO, Mid Stance (Mst), and Mid Swing (MSw)). This algorithm utilized angular velocity data from a sensor positioned on the shin and data acquired from floor switches.

In the present study three IMUs and two footswitch insoles were used to record the human walking data. Then, a method was proposed to accurately estimate the key instances during walking and identify four gait phases, including: Stance, Swing, Double Support, and Single Support phases, for both right and left legs. Subsequently, the acquired data was labeled accordingly to train a neural network.

This research introduces a novel approach for gait phase detection and classification based on data of only one IMU mounted on the lower back, which can facilitate the data collection in Robotics and Rehabilitation.

Data Acquisition and Test Protocol

This study employed the FUM-WIMU sensor, an in-house developed 9-axis IMU at the FUM Center of Advanced Rehabilitation and Robotics Research (FUM CARE). Additionally, two rubberized insoles whiched are synchronized were equipped with push-button switches for data acquisition, and the FUM-IMU software [18] was utilized to activate the system and store the acquired data. MATLAB R2021a was also used for data processing, while Python programming language and Pytorch framework were employed to implement the neural network. In order to collect data, a system of 3 FUM-WIMU sensors connected to a central computer for data acquisition and storage was used. One sensor was placed on the lower back at the L4-L5 level, as shown in Fig. 1, and the two others were laterally attached to the subject's shanks using Elastic belts (Fig.1). Additionally, two insoles placed in the ordinary testing shoes were connected to the foot-mounted IMU boards via GPIO pins of the ESP8266 module. This way, the data measured by IMUs and insoles were synchronized and sent to the central computer. Fig. 1 illustrates the components of the utilized setup.

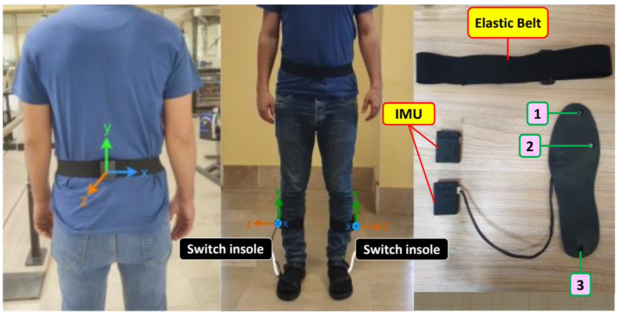

Figure 1. Components of the experiment setup and lower back IMU alignment. Numbers 1, 2 and 3 indicate the embedded switches

Thirteen adult males and one adult female (Table 1) were requested to wear the setup and walk on a straight, smooth surface along a 7-meter path at their daily preferred speed. Subjects were healthy when conducting the experiments. During the tests, data of IMUs, consisting of the linear acceleration, angular velocity, and the orientation of the sensors and insoles were recorded at 225 Hz.

Table 1. Subject Characteristics

	Subjects (*n*)	Age (year)	Height (m)	Weight (kg)
Male	13	23.5 ± 0.7	1.77 ± 0.0	73.2 ± 4.5
Female	1	21	1.66	56
Total	14	23.4 ± 0.1	1.76 ± 0.0	67.9 ± 5.7

In the preprocessing stage, a second-order Butterworth low-pass filter with a cutoff frequency of 6 Hz was applied to the linear acceleration and angular velocity data. Figure 2 compares the filtered and raw linear acceleration and angular velocity data along the z-axis measured by the lower back-mounted sensor. To prevent any potential time shifts due to data loss, the received data from insoles and foot-mounted sensors were resampled relative to the size of the lower back sensor's time vector.

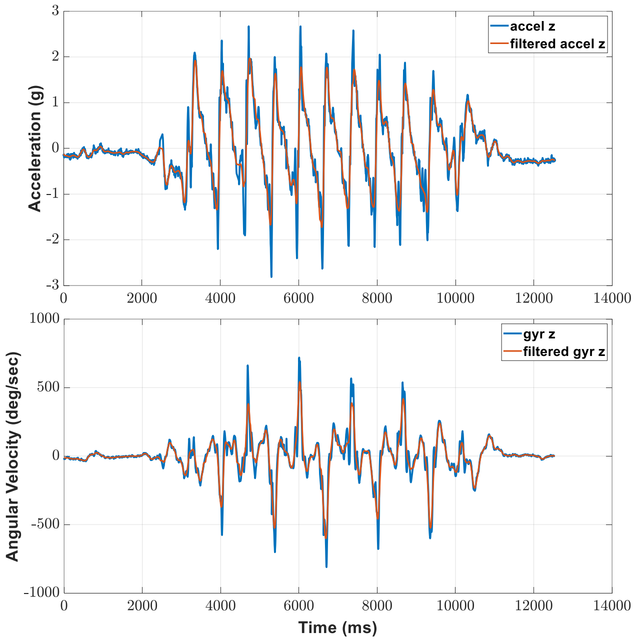

Figure 2. Raw and filtered IMU data

Phase Detection and Labeling

Human walking consists of repetitive and periodic steps. The time interval between two consecutive HSs of one foot is considered as one step, further divided into two phases: Stance and Swing. The Stance phase begining with the heel striking the ground continues until the toe lifts off the ground, while the remainder, from TO to the next HS, is called the Swing phase. The distance between the first HS of one foot and the TO of the opposite foot is known as Double Support, while the Swing phase of the foot under investigation is called Single Support. Therefore, the HS and TO moments serve as distinguishing points between different motion phases (as shown in Fig. 3). As a result, if a method can be used to find the moments of occurrence of these points during each gait cycle, it can be used to classify and assess the movement phases.

In the current work, the foot-switch insole was employed to detect the key cycle points of HS and TO for the both legs, label the acceleration and angular velocity data, and identify the time intervals of each step. Specifically, the activation time of switch No. 3 shown in Fig. 1 indicates the HS point, whereas the moment of deactivation of switch No. 1 indicates the TO point. The sequence of these points during a step, for example, for the right foot, is such that, when the heel of the right foot first hits the ground, a few moments later, the tips of the toes of the left foot are separated from the ground. After a few moments, the heel of the left foot is also placed on the ground and then it is time to separate the toes of the right foot from the ground. Since two foot sensor switches were used in this experiment simultaneously, these two points were identified for both feet in each step, and this information was utilized to determine the phases and their respective timing.

In order to recognize the mentioned time points, the zero or one interval of the corresponding switches is not important, but the moments when switches number 1 become inactive and the moments when switches number 3 become activated are important.

By comparing the insoles data and the recorded acceleration and angular velocity, it is evident that the local extremums of the linear acceleration data along the z-axis of the lower back sensor (as shown in Fig. 1) closely correspond to the observed HS and TO points, in such a way that, within the time interval of each stride, the linear acceleration data has four distinct local extremums. Specifically, two consecutive minimums are close to the time points, when switches No.3 in the insoles are activated for the first time in each stride. These points can be considered as HS points. Similarly, two consecutive maximums are close to the points when switches No. 1 in the insoles are deactivated for the first time after the recent activation. These points can be considered as TO points (see Fig. 3).

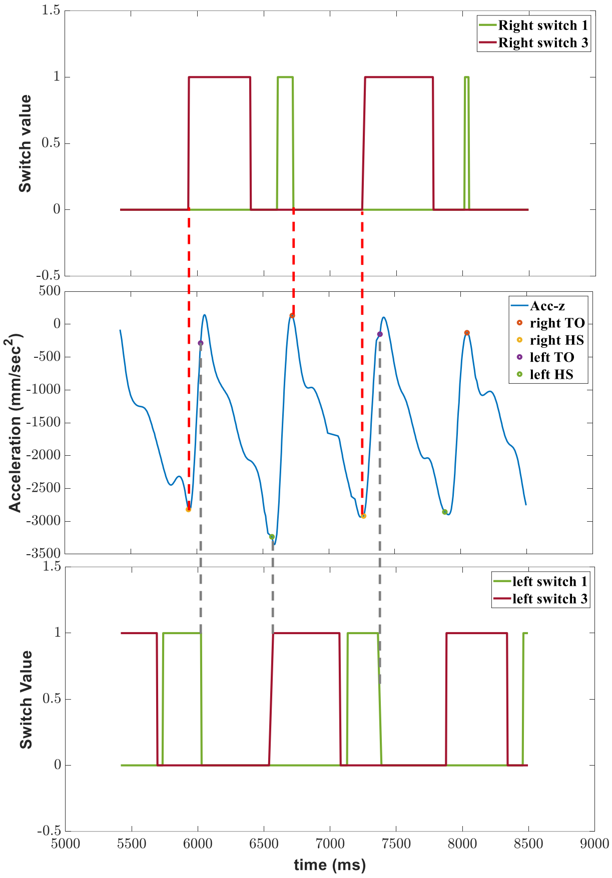

Figure 3. Detection of HS incidence on the acceleration data of the lower back sensor

The peaks of the z-axis acceleration data from the lower back sensor were used to identify the HS and TO events (see Fig. 4). We then compared them with the events detected by the insoles in all the tests. Table 2 shows the time differences between the two methods.

Table 2. Time differences between switches and peak detection

Point	Mean Difference(sec) ± std
Right HS	0.0162 ± 0.0108
Right TO	0.0185 ± 0.0144
Left HS	0.0207 ± 0.0102
Left TO	0.0167 ± 0.0119

In the next step, a computer script was developed in MATLAB R2021a based on the collected information. This script identifies the peaks in the acceleration data of the back lower sensor along the z-axis and determines their occurrence order followed by labeling them as HS or TO.

According to the explained approach, The mean time difference between proposed method and the insoles was 18ms, as shown in Table 2. This is a reasonable value for accurately detecting the HS and TO events for both legs, given a normal walking speed of 1-1.6 m/s, so the presented algorithm performed well in detecting the critical points of movement. However, in the absence of foot-switch insoles, the proposed method automatically does not enable to recognize whether the detected points are related to the left or right foot. Therefore, upon labeling the IMU data by means of the aforementioned algorithm, a neural network has been trained to detect the phases using the IMU data in the absence of foot-switch insoles.

Neural Network Model and Gait Detection

Considering that the proposed labeling algorithm is solely based on detecting peaks in the z-axis acceleration data of the lower back and the data trends between these key points are similar for both legs, it may not suffice for distinguishing between the phases in the left and right legs. Therefore, in addition to the linear acceleration data, the orientations have also been used in training the neural network. By use of the orientation data, a more comprehensive and accurate representation of the gait phases can be achieved, which enables a better differentiation between the phases in the left and right legs during the training process.

For training the neurual network the linear acceleration and oritentations data of a randomly selected subject were used as the evaluation set, while the remaining data were used as the training set. This division ensures that the evaluation set remains independent and can be used to assess the performance of the trained model.

To prepare for the model training, all the data were normalized in range of -1 to 1. This normalization helps standardize the data within a consistent range, which improves the training process and the generalization capabilities of the neural network. A sliding window approach was applied to extract the training sequences from the data. The signals were divided into sequences of 1280 samples long. These sequences overlap with each other on a length of 640 samples. This window size and overlap configuration allows for identification and analysis of the local patterns in the data. This technique makes multiple sequences of acceleration and orientation data, which can be utilized in the neural network training and the subsequent analyses.

The architecture of the proposed model is shown in Fig. 5. The selected network for this research is a Convolutional Neural Network and Gated Recurrent Unit (CNN-GRU) architecture. In the first layer of this architecture, a CNN layer and a Group Normalization (GroupNorm) layer were employed to reduce the sequence length from 1280 to 320 samples, bearing in mind that the recurrent neural networks forget the information over long sequences. In the second layer, a GRU layer was employed, considering that the labeling approach used in this study is dependent on the previous signals. Additionally, GRU was chosen due to its suitability for datasets with limited data and ability to manage long sequncees better than simple Recurrent Neural Network (RNN). Moreover, a bidirectional structure was applied to the GRU model, which enables the signal analysis in both forward and backward directions.

In the last block of network, a set of four linear layers was employed, where each layer is specifically responsible for estimating one of the intervals of swing/stance and single/double support of the right and left feet. Then an Upsample layer was used to resize the predictions to the input size.

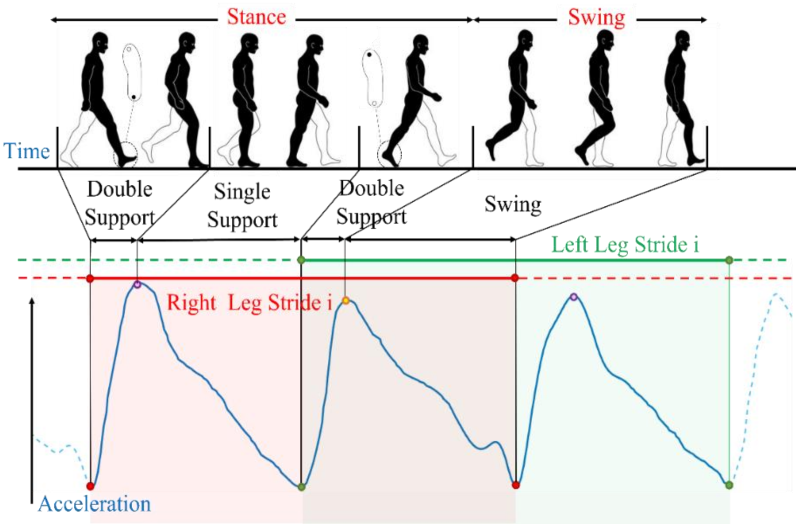

Figure 4. A complete one cycle of human walking gait and its classification based on represented algorithm

Finally, a loss function calculated error between all predictions and targets. It is noteworthy that dropout layers were also applied between all layers for regularization purposes.

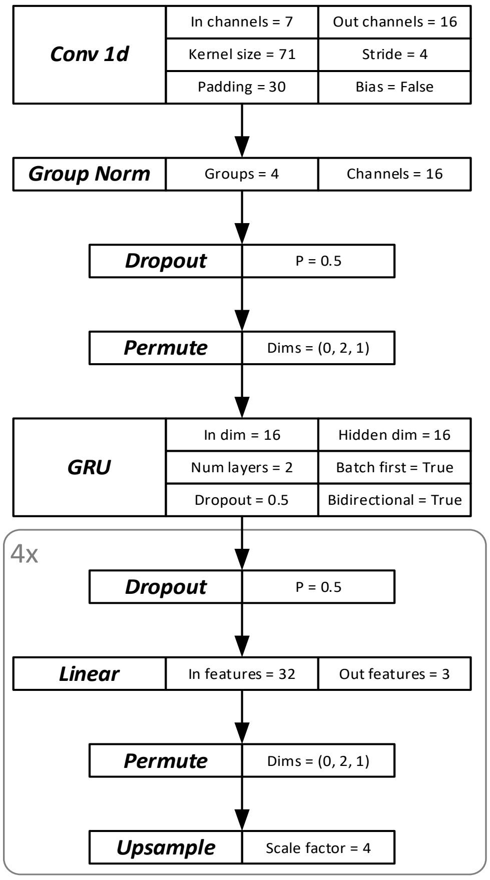

Figure 5. Neural network architecture

The adopted loss function for training was Cross Entropy. This function computes the loss values for each one of the linear layers. Summation of these loss values gives the overall model loss. For optimizing the neural network weights, AdamW algorithm was employed with weight decay set to 0.05. The model was trained for 1000 epochs, and during the training process, the learning rate linearly increased from 10^{-5} to 10^{-4} in the first 50 epochs. Subsequently, the learning rate was reduced using the CosineAnnealingLR algorithm for the remaining epochs. At the end, the model performance was evaluated using two metrics: the mean Intersection over Union (mIOU) as represented in (1) and the accuracy as defined in (2). That is

$$mIOU = \frac{Intersection\ of\ predicted\ and\ real\ phase}{Union\ of\ predicted\ and\ real\ phase + \epsilon} \qquad (1)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (2)$$

where TP, TN, FP and FN stand for true positive, true negative, false positive and false negative, respectively, and ϵ is small positive fractional value to prevent the denominator from becoming zero. Moreover, the mIOU value represents the average intersection over union between the true phases and the predicted phases.

Results and Discussion

In the present study, data on the walking patterns of 14 healthy individuals were collected using a system consisting of 3 IMUs and insoles with footswitch. One IMU was mounted on a subject's lower back while the two IMUs were mounted on the subject's shanks. The output of the three IMUs with that of the foot switches were compared. It was determined that the one IMU on the subject's back best correlates with the foot switches timing. A labeling method, referred to as "Peak Detection" was introduced. The proposed method identifies various phases of individuals' movements for both legs based on the single IMU, mounted on the subject's lower back. According to the results in Table 2, the proposed method resulted in detecting 18ms on average for the mean difference. Considering a normal speed of about 1-1.6 m/s, the 18ms seems to be acceptable to effectively identify the key cycle points of HS and TO for the both legs. The slight differences between the measured times with switches and the values calculated by the peak detection method are attributed to the fixed size of the insole for all subjects and the distance of switch placement on the insole relative to its edges, leading to delays or advancements in the moments of foot contact and lift-off.

In the next step, the proposed data labeling method was utilized to train a neural network responsible for automatically detecting gait phase cyles. The model's performance was reported to have an accuracy of about 85% for all phases according to Table 3. Clearly, the model accuracy can be improved by adding additional training data

Table 3. Accuracy and mIOU of the CNN-GRU

	Swing/Stance		**Double / Single Support**	
	Accuracy (%)	mIOU (%)	Accuracy (%)	mIOU (%)
Right Leg	78.82	65.00	86.00	70.35
Left Leg	86.68	76.60	87.47	71.86
Mean (%)	82.75	70.80	86.74	71.10

Conclusion

This work presents a simple method for gait phase detection based on data from only one IMU mounted on the subject's lower back. It has been demonstrated that the linear acceleration of the lower back sensor is beneficial for gait phase detection. Building upon this, a novel method has been developed to identify moments of heel strike (HS) and toe-off (TO) for both legs. The proposed method accurately estimates the key instances during walking and can classify the four gait phases for each leg. In the next step, a neural network is trained for gait phase detection. The proposed method provides reliable and accurate approaches for gait phase detection, which can be particularly useful in gait analysis and rehabilitation applications.

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