Gait Event Detection Using Inertial Sensors and Fast Intelligent Algorithms

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Abstract

Gait analysis is the movement study of animal locomotion, especially humans, to measure body movements, body mechanics, and muscle activity. Movement and gait analysis is beneficial for identifying, planning, and treating the movement of people, especially injured individuals. This study aims to detect human gait phases using accelerometer and gyroscopes data provided by the inertial sensors and analyze them using intelligent algorithms. Gait analysis using these sensors is a low-cost and efficient way to obtain helpful information about this process.

The purpose of this study is to develop a fast and intelligent algorithm to detect gait phases of unhealthy subjects and healthy individuals. Most articles in the literature used high computational complexity algorithms to detect phases, but these algorithms do not seem efficient for use in the long term due to high energy consumption. Therefore, we used a less computational expensive machine learning model named logistic regression. We also developed a threshold-based algorithm that has minor computational complexity. Note that in this study, the parameters of the threshold-based algorithm are optimized using the Genetic optimization algorithm, so it is an optimized threshold-based algorithm. Finally, experimental tests were used to evaluate the performance of the proposed algorithms and compare them to make a trade-off between performance and computational complexity and ultimately choose the best algorithm. In this study, the algorithms were tested on three healthy individuals with different walking speeds and three individuals with different movement disorders, including slap, steppage, and hemiplegic gait.

Keywords: Gait pahse detection, Rehabilitation, Inertial Measurement Unit, Machine Learning, Intelligent algorithms

1 Introduction

Gait analysis has become very important due to its vast applications. It is used in various fields, including sports, health care, rehabilitation, biomechanics, and robotics [1]. Athletes' performance defects can be identified and improved by performing multiple sports exercises in sports. In health care, various gyroscopes and accelerometers can identify and differentiate healthy people from people with sagging foot or knee arthritis. In rehabilitation, it can create better and more scientific conditions for the rapid recovery of patients and people with specific gait patterns due to diseases

such as MS, Parkinson's, and heart attacks [2]. It is also possible to help people who have a disorder in their gait cycle due to injuries and degenerative injuries, musculoskeletal injuries, and neuropathy. In biomechanics, much research has been done with the help of wearable devices and sensors to detect gait phases [3]. The field of robotics also uses gait analysis to maintain the balance of the robot during gait, which requires timely detection of gait phases.
In different researches and studies, the gait phases cycle is categorized differently. We considered four categories: Mid Stance, Terminal Stance, Swing, and Loading Response. These gait phases are shown in Fig. 1. Four events transition between these phases are: Heel off, Toes off, Heel strike, and Toes strike.

Four methods of Support Vector Machine, Random Forest, Extremely Randomized Trees, and Logistic Regression was used in Zdravevski *et al* [4]. The result showed that the Logistic Regression algorithm had better performance compared to other methods. Phase-detection accuracy in this paper is over 90%. Five inertia measurement sensors were used on the chest, waist, right wrist, right knee, and right ankle of ten different people to detect gait phases in Dehzangi *et al*. [5]. The DCNN algorithm was used to detect the gait phases. The researchers found that the detection accuracy using angular velocity data is higher than the acceleration data. The detection accuracy of this paper with the help of DCNN was 93.88%.

In Zhang *et al* [6]. data were collected using a device that includes two insole modules and a data logger. The LASSO operator was used to prevent over-fitting of data as well as the SVR algorithm. In this paper, the use of the SVR algorithm was more accurate than the LASSO algorithm. The inertia measurement sensors have been used to collect data from subjects who do various sports activities in Ghazali *et al* [7]. Sports activities included walking, running, and jumping. In this study DT, DA, SVM, and KNN methods were used. The SVM algorithm achieved 91.2% detection accuracy, while other algorithms for detecting these activities reached less than 90% accuracy. Rastegari *et al*. [8] used accelerometers data of healthy elderly and subjects with mild Parkinson's disease to collect data. A MIGMC (Maximum Information Gain Maximum Correlation) approach was used to detect gait better. Various machine learning methods such as SVM, Random Forest, Bagging, and AdaBoost were applied to the data. This paper showed that the AdaBoost way for standardized data is nearly 98% accurate, and the Bagging method accuracy is 96.7% . In [9], Cheng *et al*., the aim was to diagnose Parkinson's disease early. Patient data were collected by accelerometers installed on mobile phones. A nine-layer DNN was used to detect gait phases and activities. The detection accuracy of this DNN reached 98%.

Most reviewed articles aimed to identify the gait phases of healthy subjects, and their algorithms may not perform well on subjects with gait disorders. We also review several articles whose primary purpose is to detect the gait phases of subjects with gait disorders.

An article written by Pérez-Ibarra *et al*., 2019 [10], Uses an IMU sensor mounted on the back of the heel. The IMU sensor was mounted on three subjects (a healthy person, a hemiparetic patient, and a myelopathic patient). In this research, several rule-based algorithms have been used to identify gait phases in real-time. These algorithms have achieved high accuracy for three categories of healthy individuals (0.99 F1-Score), hemiparetic (0.97 F1-Score), and myelopathic (0.96 F1-Score).

In [11], Sánchez Manchola *et al*., a single IMU sensor (placed on the foot) and FSR force-sensitive sensors (on the sole of the shoe) were used. Two threshold-based methods based on demarcation and machine learning method by Hidden Markov model (HMM) algorithm were used to detect gait phases. The subjects included nine healthy individuals and nine individuals with hemiplegia gait disorder. The accuracy of gait phase detection in HMM method was more than threshold-based. The maximum accuracy with HMM method was 81.44%.

In another paper presented by Yin *et al*., 2019 [12], two small wearable wireless sensors called Shimmer and 3 IMUs were used to collect data mounted on both legs of the test subjects. The accuracy of ANN algorithms on 15 participants when using BPNN, LSTM, CNN reached 86%, 81%, and 93%, respectively. In this study, five types of gaits related to people with various gait disorders and one for healthy people have been studied. The accuracy of the CNN algorithm was reported to be 93% for Steppage gait and 97% for Hemiplegic gait.

In most articles related to the gait phases detection of subjects with movement disorders, algorithms based on artificial neural networks have been used. Although the performance and accuracy of these algorithms are much better than other algorithms, due to their high computational complexity, they may not be suitable for use in gait phase detection in real-time and long-term applications. Since the process of walking is performed quickly, it is required that the detection calculations be done in a short time. Therefore, using such complex calculations to make phase detection does not seem efficient due to being prone to delay and high energy consumption. This study aims to develop an algorithm for the gait phases detection of the subjects with movement disorders, which has appropriate accuracy and less computational complexity than neural networks and can perform phase-related calculations with minor delay and much less energy consumption. Thus, we develop a machine learning-based algorithm called logistic regression, which has much less computational complexity than deep-learning algorithms such as artificial neural networks. Another detection algorithm that has low computational complexity is the threshold-based algorithm. In this research, we also develop this algorithm and optimize its parameters with the help of Genetic optimization algorithm. Finally, we compare the overall performance of these two proposed algorithms and introduce a detection algorithm with appropriate accuracy and low delay by making a trade-off between the accuracy and delay of these two algorithms.

2 Methodology

2.1 Data acquisition

In this study, two smartphones, a PC, and an Internet wireless modem were used for collecting data. First, a mobile phone with IMU + GPS Stream application is used for data collection instead of sensors. A data sample is recorded every 0.02 seconds in this app, so the sensor's sampling rate is 50 Hz. With the help of this installed sensor on the mobile phone, angular velocity and linear acceleration angles are taken in real-time. Fig. 2. shows how to install the smartphone on the shoe. Then IP Webcam software is installed on the second phone to instantly take a video of the walking steps and use the photos taken in a row to detect the actual gait phases, and they can be used as a ground truth signal. We integrate these instruments using a wireless modem and MATLAB (The Math Works, Inc.) codes. Performing the data validation requires the photos of the second phone to be checked and labeled according to table 1. It is helpful to perform an operation called data preprocessing before using the data. This operation includes two stages of designing a low-pass filter and data normalization, which are presented below.

2.2 Moving average low-pass filter

The data collected from sensors usually have sharp peaks and bottoms caused by the sensor's noise. If these noises are considerable, it can distort the signals and reduce their value, thus harming the performance of detection algorithms. So, in this research, a moving average filter is used to eliminate the possible noise on the signal data and soften the graphs. This filter is a low-pass filter with infinite impulse response (IIR).

This filter is mainly used to smooth a set of sampled data or signals. This type of filter takes two inputs of the desired signal and a time interval (window), averages the data placed on a window, and makes the result equal to the data in the middle of that window. As the window length increases, the smoothness of the signal increases too. However, too much window size may cause the signal information to be lost. Therefore, a trade-off is needed through trial and error.

The frequency response of the filters can be shown as a result of dividing a polynomial, as shown in Eq. (1)

$$H(z) = \frac{\sum_{n=0} b(n) z^{-n}}{\sum_{n=0} a(n) z^{-n}} \tag{1}$$

IIR filters have a series of nominator coefficients, but the denominator coefficient is always equal to one. Therefore, there are only frequency response form coefficients. In the moving average filter, the number of these coefficients depends on the length of the time window and is obtained using Eq. (2). Note that in Eq. (2), N refers to the size of the time window, and ones (N * 1) refer to vectors of length N with all elements equal to one.

Table 1 Numbers which were used to represent gait phases

Label Number	Gait Phase
1	Mid Stance
2	Terminal Stance
3	Swing
4	Loading Response

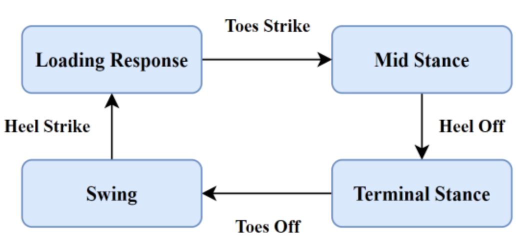


Fig. 1. Gait phases of a healthy person

Fig. 2. The frame holds the smartphone firmly to use its IMU sensor. Coordinate axes of the phone are also shown.

$$b[n] = \frac{ones(1 \times N)}{N} \quad (2)$$

Therefore, the frequency response of the moving average filter is as shown in Eq. (3):

$$H(z) = \frac{\sum_{n=0} \frac{ones(1 \times N)}{N} z^{-n}}{1} = \sum_{n=0} \frac{ones(1 \times N)}{N} z^{-n} \quad (3)$$

Unlike the offline tests, In the online tests and real-time detections, the signals from the sensor are not available from the beginning to the end, and only the previous data and the current data are available. Therefore, the filter frequency response relations cannot be used to apply the filter to the signals. Assuming the window length equals five, the solution proposed for these filter applications to online data is to leave five (equal to window length) of the initial sensor data unchanged. By obtaining the sixth data, we can average the last five data, and the result should be placed in the data number six. This process is done for all subsequent data and the five data before it. Therefore, an approximate but accurate solution can be achieved to implement the moving average filter for real-time applications.

2.3 Normalization

The data is normalized to neutralize the walking speed effect and the effect of data with abnormal values. The normalization of hypothetical data called X is performed using Eq. (4). In this Equation, μ represents the mean of the X data. In this relation, all X data can be projected onto [-1, 1] range, and this practically eliminates the effect of the range of X values, which means that the detection algorithms act independently upon different walking speeds. Note that a same approach as mentioned in filter design, is used to employ this equation in our real-time application.

$$\overline{X} = \frac{X - \mu}{Max_X - Min_X} \quad (4)$$

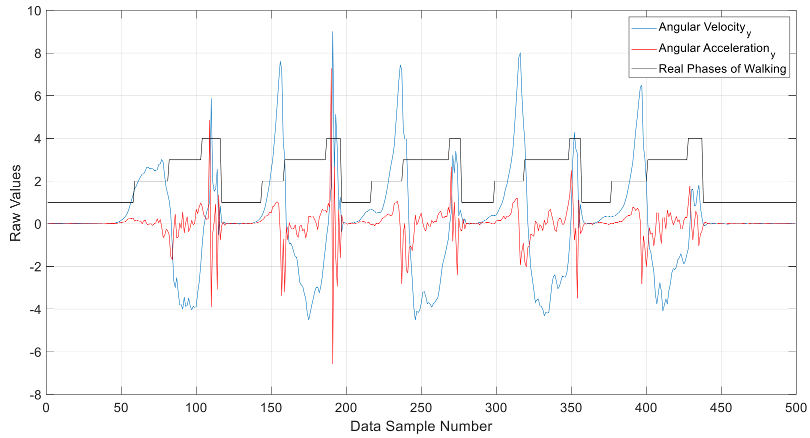
2.4 Machine learning model

Pérez-Ibarra *et al*. used a linear classifier algorithm and support vector machine as their machine learning model and gained 0.988 F1-score on healthy subjects and 0.958 F1-score on unhealthy subjects [13]. In our research, we use logistic regression algorithm and the one-vs-all method. Logistic regression is one of the binary classification algorithms, which means that it can recognize data from two different categories and classify them. However, there are four classes or phases in gait phases recognition. The one-vs-all method is the solution for using logistic regression in problems with more than two classes. This method works such that for each class, a standard logistic regression algorithm is developed with label categories equal to one meaning belonging to that phase and a label equal to zero, meaning not belonging to that phase. After developing four logistic regressions for all existing classes, the value of its hypothesis function is calculated for all classes to determine what phase a particular data x belongs to. Finally, the data belongs to the category with the highest value of the hypothesis function.

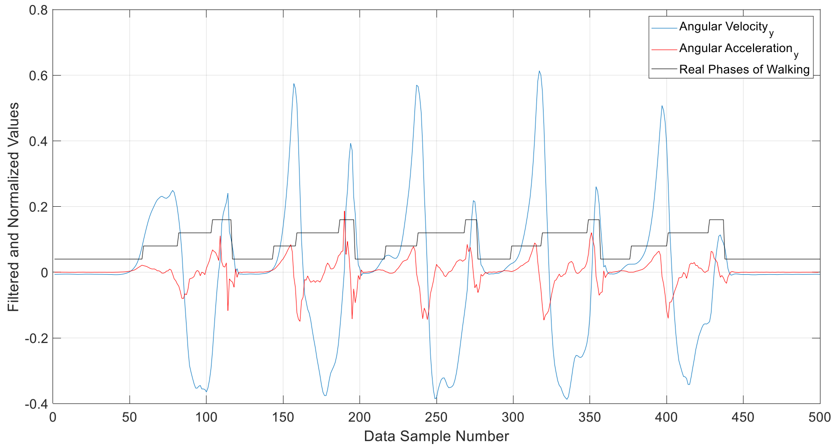
2.5 Implementing Logistic Regression

The first step to implement this algorithm is to select the data features. Feature selection directly impacts the performance and accuracy of the detection algorithm. After various trials and errors, it was found that the angular velocity_x, angular velocity_y, angular velocity_z, total or resultant angular velocity, Linear acceleration_y, Angular acceleration_y features lead to the best performance.

In the next step, a labeled dataset is used. It is divided into four different datasets, each related to a specific gait phase, and shows whether each data belongs to that gait phase (label = 1) or not (label = 0). Note that these relations are in a six-dimensional space (equal to the selected features). In Fig. 4. the black markers indicate the label equal to one (i.e. belongs to that phase), and the yellow markers indicate the label equal to zero (i.e. does not belong to that phase). The data presented in this figure was obtained from three separate data samples of a subject walking at an average speed of 1.5 m/s.



(a) Raw values



(b) Filtered and normalized values

Fig. 3. Angular velocity_y (blue), angular acceleration_y (red) and validated gait phases (black) at raw values (a) and after (b) Filtration and normalization

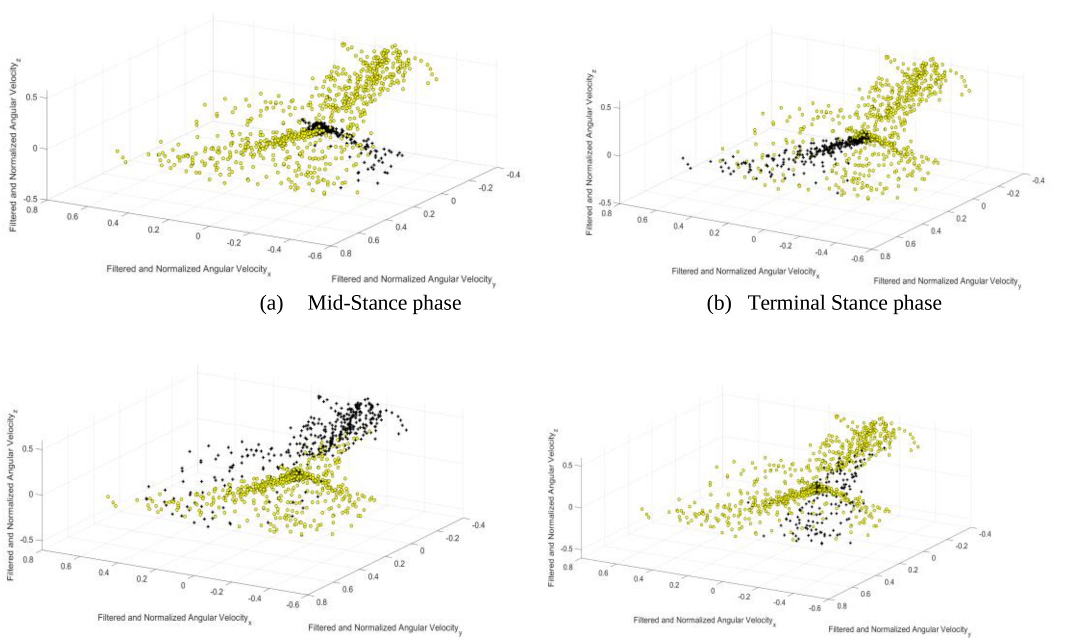
After training the algorithm for each gait phase, a theta vector is obtained. This vector represents an area that if a particular data is located in that area, that data is considered a positive label for that gait phase, meaning that specific data belongs to that gait phase. In order to determine whether a particular data phase is related to which phase, using the obtained theta parameters, the probability of placing that particular data sample in each of the four gait phases is calculated. Finally, that data sample belongs to a category with the most probability.

2.6 Threshold-based algorithm

One of the common detection algorithms in literature is the threshold-based algorithm. In this algorithm, with the help of a series of numerical thresholds for IMU sensor data, several rules for detecting gait phases are obtained. These rules are then applied to the data received by the sensor, and phase detection is performed.

In this approach, two steps are important: extracting the rules, and choosing the thresholds. For the first step, i.e. determining the rules, examining the graphs and the data obtained from the sensor is needed. By exploring these graphs and the validated phases graphs, we can determine that each moment of the data diagrams is related to which gait phase. Using this manner, rules for gait phase detection can be derived. For the second step, i.e. choosing the numerical thresholds for the extracted rules, it is still possible to estimate some of these parameters by examining the data graphs, but this is not an optimal way. The proposed approach uses *the Genetic optimization algorithm* to find the optimal values of these parameters.

Fig. 3. shows the angular velocity curves of the foot in the y-direction, i.e. perpendicular to the sagittal plane, as well as the diagrams of the actual gait phases obtained by validation with the camera and IP Webcam software. Note that, in the threshold-based approach, the moving average



(a) Mid-Stance phase (b) Terminal Stance phase

(c) Swing phase (d) Loading Response phase

Fig. 4. display of labeled data for each gait phase in a three dimensional space. the black markers indicate the label equal to one (i.e., belongs to that phase), and the yellow markers indicate the label equal to zero (i.e., does not belong to that phase)

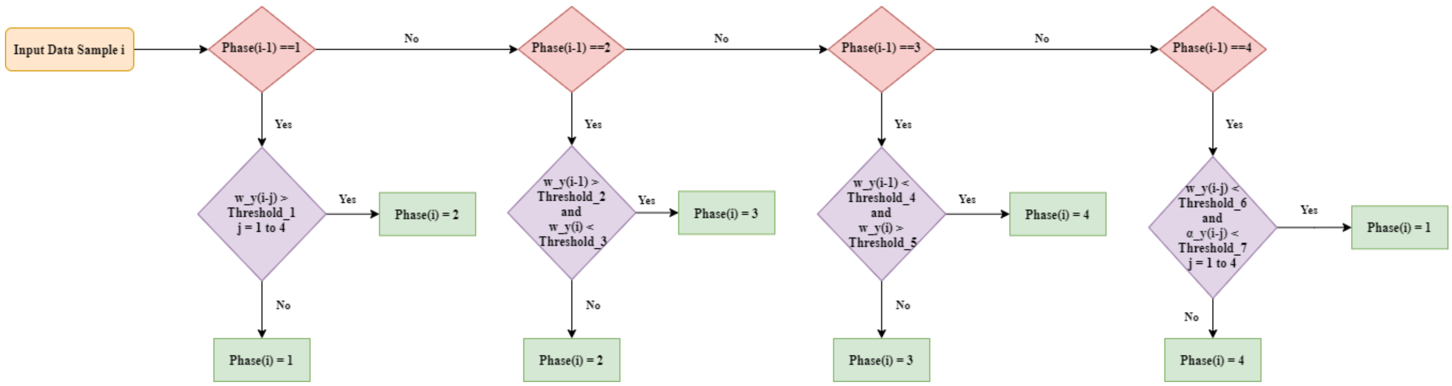


Fig. 5. Flowchart of threshold-based algorithm and its rules

filter was not used because applying a filter to data signals causes a time delay and can affect the performance of this detection algorithm. Therefore, only normalization is used in this approach, and the data are projected onto the range [-1, 1]. Fig. 5. provides a flowchart of these rules and shows how the threshold-based algorithm detects gait phases.

2.7 Genetic optimization algorithm

The genetic optimization algorithm is a metaheuristic algorithm which is used in optimization problems. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution[14]. This study defined the cost function as the number of differences between the validation matrix (actual gait phases obtained by investigating the IP Webcam pictures). The phase matrix was detected using the threshold-based algorithm. Moreover, the criterion of stopping the optimization algorithm was defined to two thousand times cost function evaluation. After finding the optimal values of thresholds with the help of the Genetic algorithm, the threshold-based algorithm can be completed, and it is called “Optimized threshold-based algorithm.”

3 Results

In this study, some experimental tests were performed on three healthy subjects and three individuals with gait disorders to evaluate the performance of the proposed detection algorithms. Healthy individuals included a 22-year-old male, a 35-year-old female, and a 55-year-old female. The unhealthy subjects tested in this study included three individuals with a slap, steppage, and hemiplegic gait disorder. Note that we did not employe actual unhealthy subjects, instead, the gait phases of these disorders was *simulated* by the authors. Three healthy subjects conducted the test with two different walking speeds, average speed (about 1.5 m/s) and above normal speed (about 2 m/s). The performance results of the two approaches on healthy subjects were obtained according to Table 2. Note that the detection error unit is in seconds. Table 3 includes the mean detection error of two approaches on all healthy subjects. Fig. 6. and Fig. 7. visualize these errors on healthy and unhealthy subjects, respectively.

Table 2 Mean of detection error of two approaches on three healthy subjects. The errors are in seconds.

Subject	Walking Speed	Heel Off		Toes Off		Heel Strike		Toes Strike	
		O.T.B	ML	O.T.B	ML	O.T.B	ML	O.T.B	ML
22 Years old, male	Normal Speed	0.012	0.016	0	0.016	0.012	0.028	0.076	0.056
	Above Normal Speed	0.044	0.040	0.032	0.028	0.016	0.028	0.072	0.060
35 years old, female	Normal Speed	0.020	0.020	0.012	0.012	0.028	0.028	0.056	0.052
	Above Normal Speed	0.020	0.020	0.012	0.052	0.016	0.056	0.064	0.088
55 years old, female	Normal Speed	0.024	0.012	0.028	0.032	0.028	0.032	0.060	0.072
	Above Normal Speed	0.032	0.028	0.020	0.032	0.032	0.040	0.056	0.064

Table 3 Mean of detection error of two approaches on all healthy subjects. The errors are in seconds.

Walking Speed	Heel Off		Toes Off		Heel Strike		Toes Strike	
	O.T.B	ML	O.T.B	ML	O.T.B	ML	O.T.B	ML
Normal Speed	0.019	0.016	0.013	0.020	0.019	0.029	0.067	0.060
Above Normal Speed	0.032	0.029	0.021	0.037	0.021	0.041	0.064	0.071

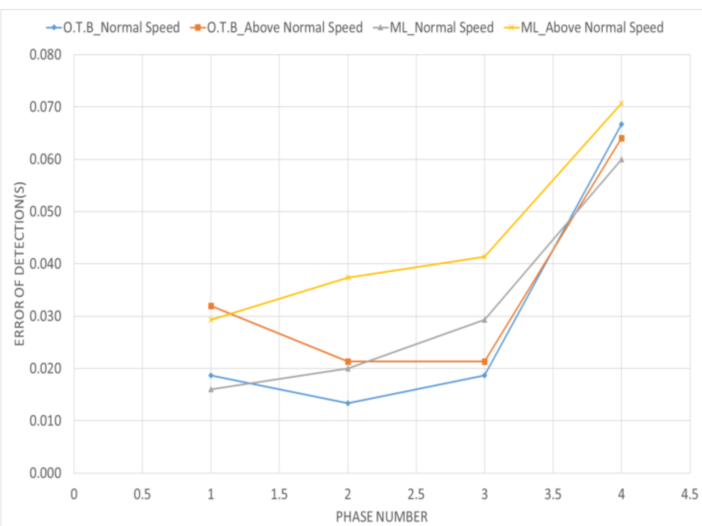


Fig. 6. Mean of detection error of two approaches on all healthy subjects

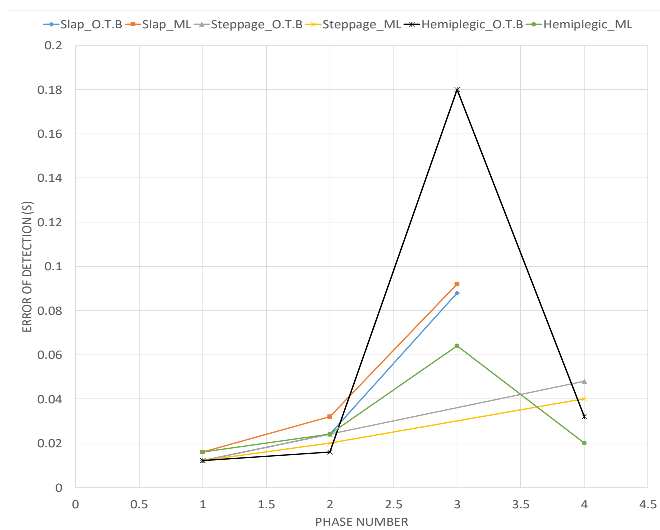


Fig. 7. Mean of detection error of two approaches on all unhealthy subjects

4 Discussion

The interpretation of the obtained results is presented in two separate sections related to healthy subjects and unhealthy subjects, respectively.

4.1 Discussion on healthy subjects

It can be seen that the detection error in the optimized threshold-based approach is generally less than the machine learning approach. Note that the detection error of heel off, which is one of the most critical phases for timely detection, is less in the machine learning approach. At the same time, the detection error of other phases is less in the optimized threshold-based algorithm. One of the reasons that the machine learning approach has more detection errors is that the model was trained on a few walking steps and for a person at an average speed. Therefore, by collecting more data and training the model on them, the model's accuracy and performance can be increased.

Another point that can be deduced from the results is that the detection error of toes strike is more than other phases. As mentioned before, this could be due to the camera's low resolution of this event. However, this gait event is the least important among the four events of the gait phases. The most critical gait events are heel off and heel strike. The performance of both approaches in detecting these two events is quite good. The advantage of the threshold-based algorithm over the machine learning approach is that it has slightly higher accuracy and lower computational complexity.

4.2 Discussion on unhealthy subjects

In this section, evaluation of the proposed algorithms on subjects with an abnormal gait is studied. In these patients, the sequence of gait phases may differ from healthy persons. Moreover, some of the phases in their gait may not occur. Nevertheless, the gait cycles of these unhealthy subjects also have repetition, making it easier to examine the gait of these individuals. Note that we did not employe actual unhealthy subjects, instead, the gait phases of these disorders was *simulated* by the authors.

a) *Slap gait:* The gait phases of this type of walking are such that the heel off and the toes off occur respectively, then the swing phase begins and continues until the heel hits the ground as a slap. It is noteworthy that the heel and toes strike occur almost instantly, and there is virtually no loading phase response.

   As can be seen from the results and Fig.7, the detection accuracy in both approaches at the moment of heel off and toes off is acceptable. This is because the heel off and toes off events in a person with slapping disorder are the same as for a healthy person. However, when the heel hits the ground, it is observed that there is a relatively large error. This is because in a person with slapping disorder, the main problem is at the moment when the heel hits the ground with a severe, slap-like impact, and the difference in the speeds of the foot hitting the ground compared to regular walking cycles causes this error. The other note is that there is no loading response phase in the walking cycle of a person with slap disorder. In other words, the moment of toes strike is the same as the moment heel strike, but in the proposed algorithms, phase number four must first be detected to enter the next phase. Nevertheless, this issue is not critical because the moment the toes hit the ground is not so important, and the most important event is the moment that heel hits the ground, which is accurately recognized.

b) *Steppage gait disorder:* In this type of gait, the person's foot does not cut off from the ground, and there is no swing phase. In other words, the foot is stretched on the ground and there is no longer the swing phase in the walking like a healthy person. The phases of walking in this type are heel off, stretching the toes on the ground (this phase is equivalent to the swing phase in the walking of a healthy person), and foot flat, which we consider being equivalent to the toes strike.

c) *Hemiplegic gait disorder:* Patients with this gait disorder cannot move their leg in a straight line on the sagittal plane, and their foot deviates from this plane after lifting the foot off the ground. In this gait disorder, all four main events, including heel off, toes off, heel strike, and toes strike, can be imagined. However, in this type of gait, all the phases occur with a brief time interval.

As can be deduced from the results, detection accuracy for three moments of heel off, toes off, and toes strike in both approaches is acceptable due to similarity of these three events to the cycle of a healthy person. However, the difference is in the swing phase, and as can be seen, the detection accuracy of this phase is low in the threshold-based algorithm. The reason for the low accuracy of this phase detection in the threshold-based algorithm is that the foot does not move on the sagittal plane and instead moves on an arched path. Also, this algorithm uses just two angular velocities and angular acceleration in the y-direction and cannot detect this phase in time. But in the machine learning model, since it uses the six data generated by the sensor (angular velocity_x, angular velocity_y, angular velocity_z, angular velocity output, linear acceleration_y, angular acceleration_y), it can detect this phase in time.

5 Conclusion

This study aims to propose an algorithm with much less computational complexity than deep-learning algorithms to detect human gait phases in real-time, emphasizing unhealthy subjects with gait disorders.

The results of applying two proposed detection algorithms to the healthy individuals were both appropriate and acceptable, and the overall performance of the two approaches was almost identical. Heel off, toes off, and heel strike events were detected in both approaches with much low error. Detection of toes strikes event in both approaches was associated with more error, which can be attributed to the difficulty of detecting this moment with the help of calibration with the camera. Finally, it was tried to test the proposed detection algorithms on people with gait disorders which is the primary purpose of this study. Concerning subjects with slap gait, the performance of the two algorithms was acceptable and similar to each other. However, the detection error of heel strike was more than other phases since the foot hit the ground at a higher speed than usual. Concerning subjects with steppage gait, the performance of the two algorithms was acceptable and similar to each other. In subjects with hemiplegic gait disorder, detection error in the machine learning model was much less than the threshold-based algorithm. The reason was that this model used more information of the IMU sensor's data provided. Generally, it can be concluded that the proposed algorithms and especially the machine learning model have acceptable accuracy in detecting critical gait phases of subjects with abnormal gait. It also has much less computational complexity and energy consumption than other algorithms such as deep-learning methods. Fig. 8. shows the schematic of the proposed machine learning detection algorithm. In order to improve the performance of the proposed algorithms, the following suggestions are provided:

- Using another validation method can help a lot to improve the performance of both approaches. For example, force plates sensors and cameras equipped with machine vision technology can be used to validate sensor data.
- Teaching the machine learning model on more data can improve the performance.

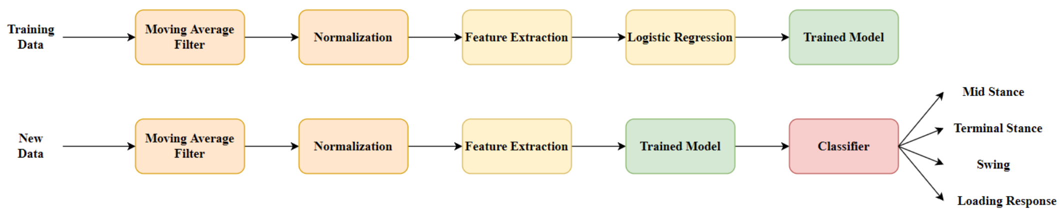


Fig. 8. Schematic of the proposed machine learning detecion algorithm

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Author Contributions

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Consent to participate

Informed consent was obtained from all individual participants included in the study.