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# Heel-Contact Gait Phase Detection Based on Specific Poses with Muscle Deformation

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***Abstract*— Gait phase detection and quantitative evaluation are significant for synchronous robotic assistance of human walking, rehabilitation training, or diagnosis of human motion state. Especially, accurate heel-contact detection in a gait cycle is a key requirement for gait analysis applications. Some techniques have been proposed by utilizing wearable devices, however, existing systems typically require precise and continuous time-series data at every single timestep for calibration, which largely increases the burden to users. Therefore, we propose a novel posing-based detection method through measuring muscle deformation, which only requires arbitrary and discrete posture data for calibration without walking. In this study, we firstly collected the posing data as the training set and gait data as the test set from participants through a FirstVR device. Then the Support Vector Machine was trained to be a two-class classifier of heel-contact and non-heel-contact phases by using the collected muscle deformation data during posing. Finally we propose an efficient evaluation system by taking advantage of OpenPose to automatically label our continuous gait data. Experimental results demonstrate the muscle deformation sensor could correctly detect heel-contact with approximately 80% accuracy during walking, which shows the feasibility of posing-based method with muscle deformation information for heel-contact detection.**

## I. Introduction

### A. Background

A technique of monitoring human gait motion is required for synchronous robotic assistance of human walking, rehabilitation training, or diagnosis of human motion state [1]–[3]. Identifying human gait phase is essential because walking is a periodic movement [4]. The gait phase consists of main two phases based on foot-contact information; stance phase that occupies 60 % of the gait cycle and swing phase that occupies 40 % of the gait cycle, as shown in Fig. 1. The heel-contact is the first phase of the gait cycle. A system using the floor force or a camera is the gold standard for extracting foot-contact information [5], [6]. However, the system has a limitation in carrying out the gait phase classification outdoor. Classification of the gait phase using wearable sensors is necessary for monitoring or assisting the human gait motion in daily life.

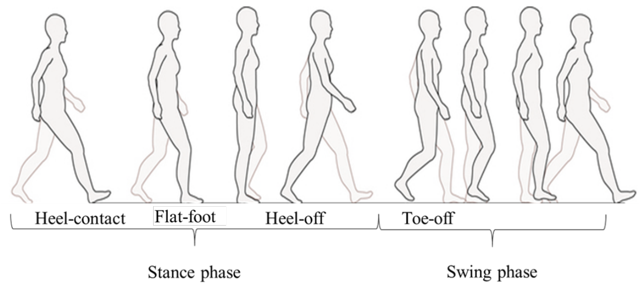


Fig. 1. Gait phase.

### B. Previous research

The gait phase detection method has been proposed mainly using foot switches [7]–[9], shoe insoles with pressure sensors [10], [11], and inertial measurement unit (IMU) [12], [13]. A thin film that can be attached on the sole of the foot or the insole, such as a force-sensing resistor (FSR), was used for the foot switches or the insoles sensor. The foot-contact information can be obtained directly with the values of the FSR. On the other hand, the foot-contact information could be estimated with the IMU that is the sensor consisting of accelerometers, gyroscopes, and magnetometers. Moreover, parameters of angles, electromyography (EMG), and force myography were also used for estimation of foot-contact information [14]–[17].

Computation technologies combined with the wearable devices have been studied. Classic methods using the foot switch or the insoles set a threshold of sensor's voltage [9]. However, the film sensors, such as FSRs, have durability issue that the reliability of sensing changes through long-term use with foot-contact impact [7], [18]. Additionally, the threshold or the placement of foot switch and the insoles

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with FSRs need be customised corresponding to individual physical difference.

In order to automatically adapt to the individual difference, machine learning-based methods (such as hidden Markov model [10], [19], and artificial neural networks [14], [15]) were applied to detection of the gait phases. However, the conventional methods based on the supervised machine learning required obtaining precise dataset and labeling it for the training phase (such as using video frames as a ground truth for training model), which puts much burden on the user. Considering use in daily life, it is required that the sensor is attached to a human easily and used without expert knowledge.

### C. Objective

In this work, we focused on muscle deformation during walking. We assumed that muscle deformation could be obtained if people stand in postures of some gait phases even though the user does not need to walk. Actually, the previous method using force myography information caused by the muscle deformation showed the usability of gait phase detection [16]. However, online detection methods of the gait phase with pose-based labeling have not been established.

The objectives of this study is to show the feasibility of the online detection system of gait phase with simple labeling method. Because heel-contact is the basis gait phase and other phases can be estimated by calculating proportion of gait cycle duration, we aimed at detecting heel-contact. We propose the machine learning-based method with muscle deformation that could obtain input-output pairs as a training dataset just by sensing human's several poses. In particular, the muscles of a calf that are related to ankle movement has a strong relation with foot-contact information [4]. Therefore, we investigated whether obtaining muscle deformation data of the calf in the several poses enable the system to detect the heel-contact.

## II. Proposed System

The proposed system is shown in Fig. 2. On the whole, the system detects gait phase while walking using muscle-deformation-based sensor FirstVR and classification algorithm based on Support Vector Machine (SVM). Each part of the system is described in following sections.

### A. FirstVR

To obtain muscle deformation information while walking, FirstVR from H2L Inc. [20] is used to detect muscle deformation from 13 channels of optical active sensors, as shown in Fig. 3. Besides, FirstVR is embedded with 9-axis inertial measurement unit (IMU). Typically, this device was used for humans' hand to detect various gestures and movements through muscle deformation sensing, including shooting in VR games, tossing the pan for VR cooking, and controlling the hand for playing the Japanese instrument [21].

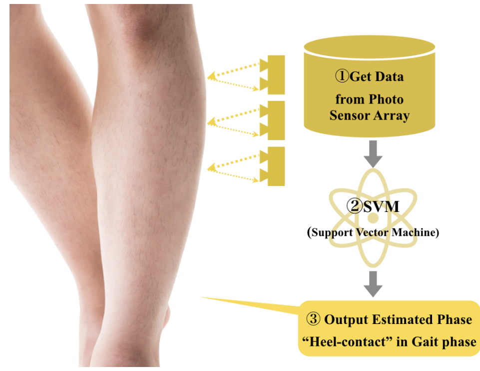


Fig. 2. Overview of the proposed system. The system detects heel-contact while walking using muscle-deformation-based sensor FirstVR and classification algorithm based on support vector machine.

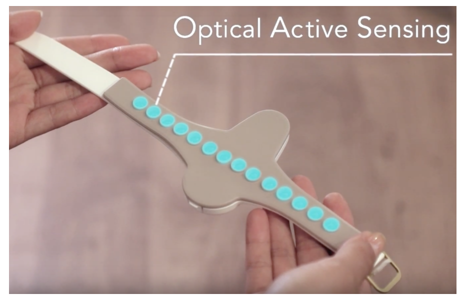


Fig. 3. Channels optical active sensing upon the FirstVR device.

Benefiting from accurate and real-time muscle deformation sensing system, the FirstVR device can also be applied to humans' legs.

### B. Detection Algorithm with Support Vector Machine

For the selection of machine learning methods aiming successful classification, training data acquired from the FirstVR needs to be analyzed. It can be non-linear and include some outliers as noise which hinders successful classification because the FirstVR is directly attached to human's leg and the position of the sensor can change while walking. Linear discriminant analysis is one of useful methods used as muscle deformation technique to carry out gait phase detection on legs [16], although the method considers all data points including outliers and is hard to apply to non-linear data structure. On the other hands, deep neural network is a powerful technique for classification of images and sounds [22], which has adaptability to complicated data structure and huge inputs. However, the application of the proposed system is walking in which real time quick response is required because of dynamic motion of muscle in legs. In such case, deep learning technique is inappropriate to use due to its high computation cost.

Finally, SVM is chosen as a proposed method in the current paper because of its adaptability to complicated data structure but small size of inputs (13 from FirstVR) [23]. The SVM generates classification results as follows:

$$f(\mathbf{x}) = \mathbf{w^T x + b} \tag{1}$$

where $x$ is a vector of input data with a size of 13 (from FirstVR); $w$ is a vector of weight parameter in SVM; $b$ is a bias parameter. The classification function $f(x)$ is consisted of them. To train the parameters including $w$ and $b$, quadratic programming problem with a cost function in which $C$ and $\epsilon$ represent parameters which control acceptance rate of classification errors and the penalty respectively is used as following;

$$\min_{w \in R, \epsilon_i} \frac{1}{2}||w||^2 + C\sum_{i=1}^{N}\epsilon_i$$
$$s.t. \quad y_i(w^T x_i + b) \geq 1 - \epsilon_i, \quad i = 1...N \tag{2}$$

where $i$ is arbitrary support vector; $N$ is the total number of the vector$y_i$ is an activation function which provides +1 or -1 depending on the result of $f(x)$. Since it accepts small error so that the SVM does not do over-fitting, soft margin SVM is used. Basically, SVM cannot handle non-linear data structure. Therefore, radial basis function (RBF) kernel is implemented as following equation:

$$K(x, x') = exp(-\gamma||x - x'||^2) \tag{3}$$

where $x$ and $x'$ represent arbitrary vectors resulting in making euclidean distance; $\gamma$ is a positive value which adjusts boundaries among classes. Humans' walk includes several gait phases (specifically three patterns are targeted in this study) thus, 1-against-the rest method was used for training the SVM whose performance can be comparably better than 1-against-1 method.

Moreover, we set the restriction of transition of label number that was calculated by the SVM. In this work, we assumed that obtaining pose of heel-contact, flat-foot, heel-off, and toe-off could classify the heel-contact phase and other phases. We labelled the heel-contact as 0, and flat-foot as 1, and heel-off and toe-off as 2 based on the ankle joint movement. If the SVM output was 1 when the previous label was 0, the system accepted this transition. If the SVM output was 2 when the previous label was 1, the system accepted this transition. Moreover, if the SVM output was 0 when the previous label was 2, the system accepted this transition.

## III. Experiment

### A. Data Preparation

This system consists of three main parts, the FirstVR, a treadmill, and a 2K camera for shooting, as shown in Fig. 4. 2K camera is mainly used to obtain the real-time videos for OpenPose detection system. The muscle deformation data of three people were collected with the FirstVR that was attached with a left lower leg. The sampling frequency of the system was 11 Hz.

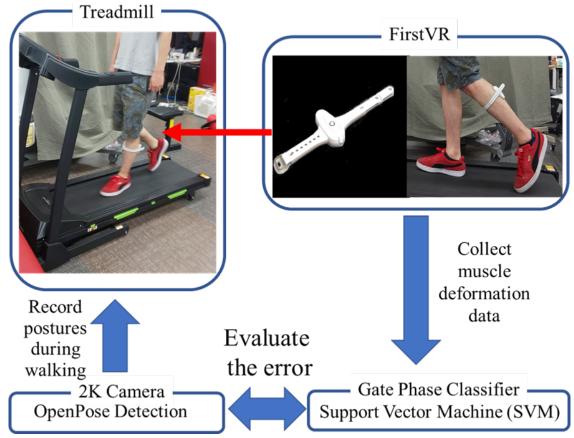


Fig. 4. Experimental setup. The FirstVR is attached to a human's left leg and collects muscle deformation data (calf muscle), while the 2K camera takes a video to capture a tow of both legs' position by processing the video using OpenPose.

We collected four posing data, that is, heel-contact, flat-foot, heel-off, and toe-off, as shown in Fig. 5. These posing data are quite easily obtained. Simultaneously, the muscle deformation data under these four poses were collected from FirstVR devices in real-time. In this work, the muscle deformation data of four poses were used for classification between heel-contact phase and other phases. Moreover, we collected muscle deformation data during walking on the treadmill to test the system performance.

### B. Protocol

This study mainly concentrates on walking with a constant speed at 3.0 km/h, which was determined based on the specification for the used treadmill. Two-phase data collection tasks was carried out as an experimental procedure. In the first phase, the four posing data were collected with FirstVR to measure calf muscles. Each posing was measured for 10 s on the treadmill.

In the second phase, gait data with FirstVR on the treadmill were measured for two minutes. We recorded videos for each person from the left side of the body. The ground-truth labels of videos are obtained using the software OpenPose [24]. By estimating the posture of the participates from the videos using Openpose, we can evaluate the detection error. We used the OpenPose to detect 25 body keypoints, and each keypoint has a pair of $\{x, y\}$. Among 25 points, we depicted the location of the left foot heel, marked by 21 in Fig.6.

### C. Performance Evaluation

The performance of the proposed gait phase detection approach is quantitatively evaluated in terms of two measurements from different aspects.

Fig. 5. Four posing data. The left top photo shows the posing of heel-contact The right top photo shows the posing of flat-foot. The left button photo shows the posing of heel-off. The right bottom photo shows the posing of toe-off.

Fig. 6. Body keypoints detected by OpenPose.

In order to obtain the ground truth of the gait phase, we estimated the walking cycle using the keypoints from Openpose. X-coordinate of the toe or heel changes periodically during walking on the treadmill as shown in Fig.7. Therefore, the time point of heel-contact can be extracted by finding extreme value of x-coordinate. We assumed that gait phase transitions at the frame when the x-coordinate value is local maximum or minimum. The frame when the gait phase transitioned (from the swing phase to the stance phase) could be found around extreme value. We checked the frame when the x-coordinate was extreme value and modified it manually if needed. Then we can obtain the ground truth label for each

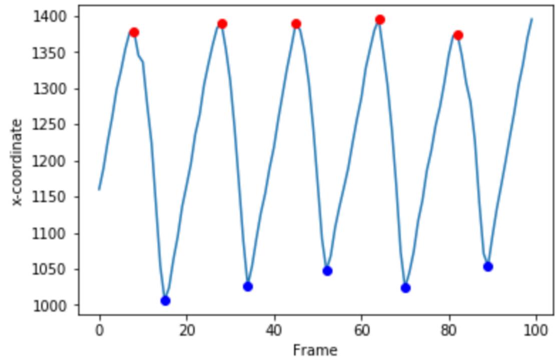


Fig. 7. Temporal change of x-coordinate of keypoint 21. Red and blue cycle denotes the maximum and minimum of coordinate value in each cycle, respectively.

frame, and we mainly focus on the heel-contact frames.

The number of gait cycles for the test data were approximately 100 for each participant. In our experiments, we defined the accuracy rate as the proportion of the cases where heel-contact are correctly detected through our proposed system among all the ground-truth heel-contact frames. On the other hand, we defined the false alarm rate as the proportion of the cases where non-heel contact are wrongly detected as the heel-contact phase through our proposed system among all the non-heel contact frames.

## IV. Results and Discussion

This section presents our experimental results and give a thorough discussion. Fig. 8 shows the effect of SVM parameters on the accuracy. The parameter of $C$ controls the weights of penalty, and the parameter $\gamma$ adjusts the boundaries among classes. By searching several candidate values, we have found $C = 1000$ and $\gamma = 0.0001$, which has the best classification performance. Fig. 9 illustrates the mean accuracy rate and false alarm rate for our system. The accuracy rate is approximately 80%, which validates 80% heel-contact frames are correctly detected through our proposed system among all the ground-truth heel-contact frames. The false alarm rate is approximately 30%, which means non-heel contact are wrongly detected as the heel-contact phase through our proposed system among all the non-heel contact frames.

To illustrate our detection system, we also visualize the training data and test data of muscle deformation for 13 channels detected from FirstVR in Fig. 10 and Fig. 11. We could observe the cyclic pattern of the data during walking and that there is a difference of values between phases in one cycle. Values in training data (posing data) had a difference between poses. Although the difference of muscle deformation in training data was smaller than the difference in test data, we assume that the difference between posing was corresponding to the difference between phases,

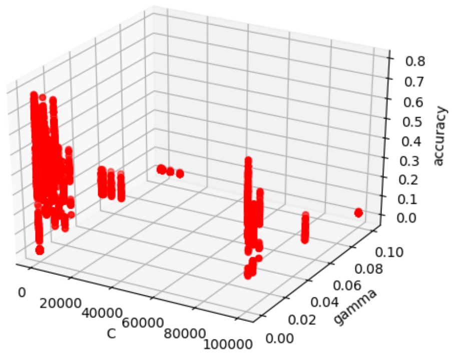


Fig. 8. The parameters of SVM for our detection system.

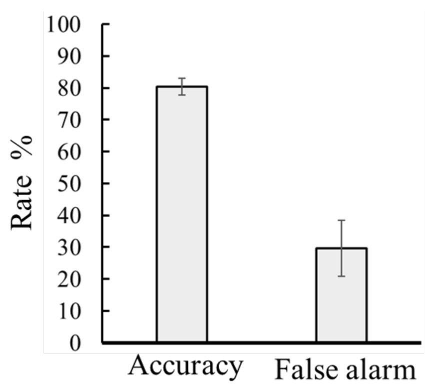


Fig. 9. Experimental result. The accuracy rate denotes the proportion of the cases where heel-contact are correctly detected through our proposed system among all the ground-truth heel-contact frames. The false alarm rate denotes the proportion of the cases where non-heel contact are wrongly detected as the heel-contact phase through our proposed system among all the non-heel contact frames.

and the proposed system could detect of heel-contact with approximately 80 % accuracy.

The feature of the proposed system was using muscle deformation sensor. Near-infrared lights of the sensor (First VR) could measure the muscle tissue structure and thus the deformation of muscles. The muscle deformation of the lower leg has a correlation with the ankle joint's movement [25]. The foot-contact information was generated by the ankle joint movement when people are walking. The bulge of calf muscle moves because of the muscle contraction or expansion to control the ankle joint. The ankle joint is in plantar flexion during the time from heel-contact to toe-off. The ankle position returns to neutral position in the swing phase. People keep the ankle joint neutral position for heel-contact. People try to change the ankle joint position to a slight plantar flexion position from neutral position at heel-

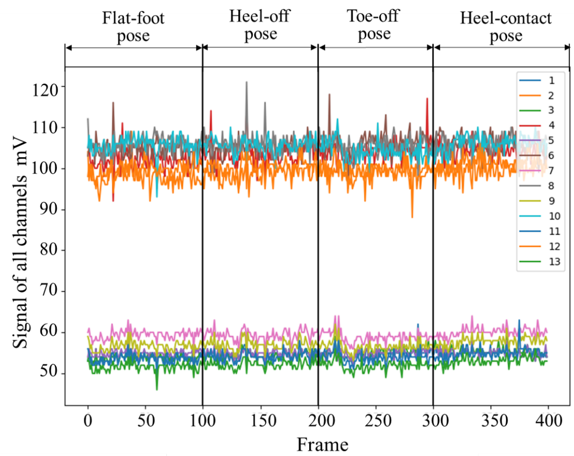


Fig. 10. Example of training data of muscle deformation for 4 posing.

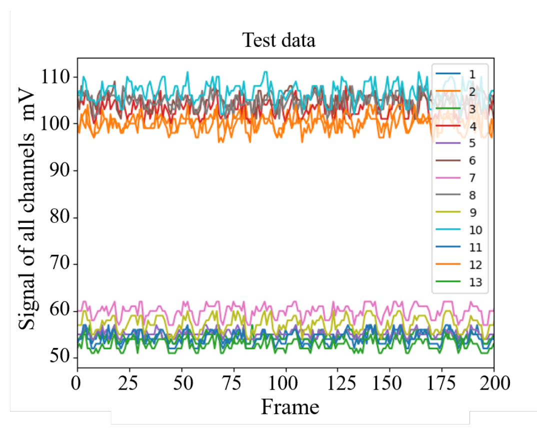


Fig. 11. Example of test data of muscle deformation during walking.

contact for loading response.

The muscle deformation information is useful for posing-based method of gait phase detection because the training dataset could be obtained without walking. We assume that the proposed method also could be applied with methods based on force myography or ultrasound. On the other hand, we assume that EMG-based method can not be applied with the proposed method because there is an inconsistence between measurement results based on force myography and EMG [26]. Moreover, EMG values could be affected by sweat during walking [27].

To the best of our knowledge, this study is the first examination of posing-based gait phase detection method. The proposed system fulfills the requirement that it can be attached to human legs easily and used without expert knowledge. Donning time of the sensor in this experiment was less than 10 s. Moreover, the calibration was carried out just by standing in four postures. On the other hand, although the accuracy of this experiment was high (80 %), this was lower than the previous methods with the machine learning method that requires labeling phase by obtaining ground-truth previously [16]. Additionally, the false alarm rate was approximately 30 %, which means the accuracy of the detection of non-heel-contact phase was approximately 70 %. We assume that the reason why the detection error occurred is because of difference of the range of sensed values between the training (posing) and test (gait) data. The degree of the muscle deformation might be different because of the slight fluctuation of postures during walking. Furthermore, we assume that repeating to obtain posing data and obtaining more types of posing data might increase degree of muscle deformation in training data. Although the accuracy could be improved in the future, this work shows the feasibility of posing-based method with muscle deformation information for heel-contact detection and the simple calibration method without labeling task.

The system has a limitation that the detection results were easily affected by the difference of attachment position or posture changes during calibration. The position of the sensor and the number of posing that could identify muscle deformation the most clearly would be worth investigating as a future work. Moreover, the filtering process could be improved because the current sampling frequency of the FirstVR sensor was low and increase the higher sampling frequency could be helpful to cut off the noise. Although only heel-contact was detected in this work, other phases basically can be derived by the proportion of gait cycle duration.

## V. Conclusion

We proposed a novel system measuring muscle deformation with FirstVR sensor to detect the heel-contact that is the basic gait phase. The system just requires some arbitrary postures for calibration without walking. In the experiment, we collected the posing data and gait data from three people. The results show that the muscle deformation sensor can correctly detect the heel-contact with 80% of gait phases. In the future, we will investigate the best position of the sensor and the best number of posing that could identify muscle deformation clearly.

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