Maximum Dorsiflexion Detection Based on an On-Board Adaptive Algorithm for Transtibial Amputees With Robotic Prostheses

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***Abstract*— Maximum dorsiflexion (MDF) is an important gait event corresponding to the maximum ankle dorsiflexion angle in each gait cycle. MDF timing plays an important role in the control of robotic prosthesis. This article puts forward an on-board adaptive algorithm to detect MDF timing of robotic transtibial prosthesis in different walking conditions (at different speeds and on different ramps) and for different users. Based on the adaptive algorithm, we can get a time-variant detection model. The framework of the adaptive algorithm is composed of: 1) training data collecting and labeling; 2) model training and real-time detection; and 3) model updating according to the detection results. Based on the adaptive algorithm, we conducted speed and ramp experiments to detect MDF timings at slow, normal, and fast speeds, and on ramps with different inclination angles (10°, 5°, 0°, −5°, and −10°). Three transtibial amputee participated in the experiments. The model training/updating time ranges from 3.6 to 4.1 s and the detection time ranges from 0.95 to 1.17 ms for different speeds and ramps. In real-time detection, there is false detection (1.67%) at normal walking speed. In addition, all MDF timings are detected correctly (accuracy: 100%) based on the adaptive algorithm. The mean detection delays are 7.23, 18.27, and 7.5 ms corresponding to slow, normal and fast speeds and 10.60, 10.30, 18.27, 10.27, and 15.63 ms for ramps of different inclination angles (10°, 5°, 0°, −5°, and −10°). Compared with the proposed adaptive algorithm, both the nonadaptive and adaptive threshold decision methods cause more false detections. The results show that the proposed approach for MDF timing detection has adaptations to different walking conditions (speeds and ramps) and prosthesis users, which indicates that the adaptive algorithm is effective and shows the potential in robotic prosthesis control in the future.**

***Note to Practitioners*—This article proposes an on-board adaptive algorithm to detect the maximum dorsiflexion (MDF) timing based on inertial measurement unit (IMU) and ankle angle sensor for robotic transtibial prosthesis users in each gait cycle. IMU and angle sensor are integrated in the prosthesis, and the adaptive algorithm is embedded in the control circuit of prosthesis. The adaptive algorithm can realize the model updating continuously for real-time MDF timing detection with collected and labeled training data. The proposed adaptive algorithm shows satisfactory adaptation for MDF timing detection in different walking speed and ramp conditions. In addition, the adaptive algorithm also shows some generalizations for prosthesis users, which are useful to improve prosthesis control.**

***Index Terms*— Adaptive algorithm, maximum dorsiflexion (MDF) detection, robotic transtibial prosthesis, time-variant detection model.**

I. Introduction

ROBOTIC prostheses can compensate the biomechanical functions of the missing limbs for people with amputations and provide assistances to their daily activities [1]–[4]. By adjusting control strategies, a prosthesis user can walk in various ambulation modes, such as walking at different speeds or on different ramps [5], [6]. How to choose proper control strategy for robotic prosthesis depends on gait event and gait phase [7]–[9].

One gait cycle can be divided into a stance phase (from heel strike to toe off) and a swing phase (from toe off to next heel strike). During the swing phase, the prosthesis needs to achieve foot clearance and reset to a desired equilibrium position [9], [10]. The stance phase can be divided into three subphases according to the ankle's biomechanics: controlled plantar flexion (CP, from heel-strike to foot-flat), controlled dorsiflexion [CD, from foot-flat to the maximum dorsiflexion (MDF)], and powered plantar flexion/push-off phase (PP, from MDF to toe off) [11], [12]. The work generated during the PP phase is more than the negative work absorbed during the CP and CD phases for moderate to fast walking speeds [11]–[14]. The function of PP is important in a prosthesis, as it can propel the body upward and forward [10], [15], [16]. For a robotic prosthesis, the control strategies for CP, CD, PP, and swing are different and designed based on the detected gait events, such as heel strike, foot-flat, MDF, and toe off [9], [10].

MDF is the gait event corresponding to the MDF angle of the ankle joint in the sagittal plane in each gait cycle; therefore, it can be detected directly from the angle signals

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of a prosthetic ankle. However, the angle signal of prosthetic ankle is not smooth during the whole gait cycle. It will bring a lot of errors, if we detect MDF timing from the sensor signals directly. Introducing a filter can improve the smoothness of the signal, but it will cause phase shift of the signal waveform, which is not practical in real-time detection for MDF timing. Setting some threshold rules can decrease the detection error according to the sensor signals directly; however, it is hard to find a set of threshold rules to adapt to different locomotion conditions (different walking speeds and ramps) and different prosthesis users. The MDF timing in each gait cycle varies as speed or ramp changes for different prosthesis users [16]–[18]. Therefore, how to realize the detection for MDF timing with adaptation has become an important issue.

In this article, we designed an adaptive algorithm based on the idea of pattern recognition to detect MDF timing. The adaptive algorithm in this study was embedded in the control circuit of the prosthesis. We recruited three persons with transtibial amputations and they wore the robotic prostheses in our research. We then conducted the real-time MDF timing detection for each prosthesis user at different walking speeds and on different ramps. To the best of our knowledge, this is the first study about on-board adaptive algorithm to detect MDF timing with robotic transtibial prostheses.

II. Materials and Methods

A. Related Work

For MDF timing detection, one frequently used method is according to the angle signals of prosthetic ankle directly to make decision based on threshold decision method. Some studies have adopted this method to detect MDF timing [1], [10]. Shultz *et al.* [1] have taken the timing when the ankle is dorsiflexed past a predetermined angle as the initial of push off (i.e., MDF timing). Au *et al.* [10] have conducted MDF timing detection by utilizing prosthetic ankle angle directly based on several threshold rules. Feng and Wang [16] have conducted MDF timing detection by combining ankle angle and reaction force information of the prosthesis. However, these studies on MDF timing detection lack of adaptation to different walking speeds, different ramps, and different prosthesis users. Though there are few studies on adaptive detection for MDF timing of prosthesis, several studies have developed adaptive (threshold rules) detection for other gait events (not for MDF). Bejarano *et al.* [19] have developed an adaptive algorithm by designing a filter by off-line analysis and updating threshold using newest gait data to detect the gait events (initial contact, end contact, and mid swing). However, their study still requires some off-line operations to get some parameters, which will bring other device (i.e., computer) and need human interference. Besides, its adaptation for different people needs further validation. Here, we utilized a pattern recognition method, instead of threshold decision method, and designed an adaptive method to detect MDF timing.

B. Robotic Transtibial Prosthesis

1) Prosthesis Prototype: As shown in Fig. 1, a commercialized robotic transtibial prosthesis produced by SpeedSmart

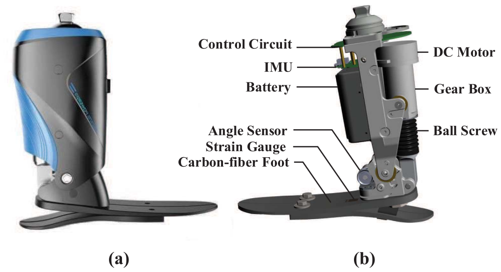

Fig. 1. Prototype of robotic transtibial prosthesis. (a) Robotic prosthesis and (b) mechanical structure of prosthesis. The components of the prosthesis include control circuit, sensors (one strain gauge, one angle sensor, and one IMU), battery, carbon-fiber foot, dc motor, gear box, and ball screw.

Company Ltd (a spin-off company of Peking University) was used in this study. The prosthesis is comprised of a control circuit, sensors [including one full bridge of strain gauge, one angle sensor, and one inertial measurement unit (IMU)] and battery, and its weight is about 2 kg. More details can be found in [2], [9], and [16]. The full bridge of strain gauge of prosthesis is used to record the deformation of carbon-fiber foot, which can be used to detect the stance and swing phases in each gait cycle [20]. An angle sensor placed at the rotational joint of prosthesis is used to measure the prosthetic ankle angle. One IMU is integrated on the shank position of prosthesis, and it can provide inclination angle (yaw, pitch, and roll), tri-axis acceleration and tri-axis angular velocity information. The direct current (dc) motor is used to drive the prosthesis with power of 150 W.

The control circuit consists of micro controller unit (MCU) and application processor unit (APU). The MCU is based on one 216-MHz Cortex-M7 processer, and its functions are to collect and synchronize the sensors signals and then pack them to the APU and execute corresponding control strategy. The APU is constructed with an integrated programmable SoC chip, which consists of two parts: a 667-MHz Cortex-A9 MPCore-based processing system and an FPGA-based programmable logic circuit. APU is designed to execute the designed on-board adaptive algorithm (data collecting and labeling, model training and updating, and real-time gait event detection) for its computation performance and then transmit the detection result to MCU.

2) Prosthetic Control: For robotic prostheses, control strategies are performed based on different gait phases [2], [16]. During the swing phase, to return the equilibrium position, a proportional-derivative (PD) position control is adopted. The principle of PD controller is as follows:

$$D_a = k_p(\theta_0 - \theta) + k_d\left(\dot{\theta}_0 - \dot{\theta}\right) \tag{1}$$

where D_a is the active controller output for motor driver, k_p and k_d are predefined constants, θ is the current joint angle, $\dot{\theta}$ is angular velocity, and θ_0 and $\dot{\theta}_0$ are the desired equilibrium angle and desired angular velocity of swing phase, respectively.

During the stance phase, a torque control strategy is adopted combined with damping control in the CP and CD. This method can result in the equal braking torque τ_{ed} due to the different duty cycle (D) of the pulsewidth modulation (PWM)

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signal [2]. It is shown as follows:

$$\tau_{ed} = k_{ed} Dn \tag{2}$$

where k_{ed} is the proportional coefficient and n is the motor speed. D is the duty cycle, and we can change D to adjust the damping control. Therefore, D can be viewed as the "damping coefficient." The controller switches between the damping functions of the CP (D_1) and CD (D_2) according to the angular rate $\dot{\theta}$ of prosthetic ankle, which is formulated as follows:

$$D = \begin{cases} k_{\text{per}} D_1, & \dot{\theta} < 0 \\ k_{\text{per}} D_2, & \dot{\theta} \geq 0 \end{cases} \tag{3}$$

where k_{per} is the percentage of the duty cycle and $\dot{\theta}$ is angular velocity. It is noted that $\dot{\theta} < 0$ and $\dot{\theta} \geq 0$ refer to plantar flexion and dorsiflexion, respectively. D_1 and D_2 are the duty cycles of the PWM signal that control the motor terminal short corresponding to the plantar flexion and dorsiflexion. The D_1 and D_2 are formulated as follows:

$$D_1 = 1 - 0.5(\tanh(s_1(\theta - \theta_{d1})) + 1) \tag{4}$$

$$D_2 = 0.5(\tanh(s_2(\theta - \theta_{d2})) + 1). \tag{5}$$

Here, s_1 is the sensitivity factor that decides the slope of the function, θ_{d1} is the threshold of plantar flexion angle, s_2 is the sensitivity factor that decides the slope of the function, and θ_{d2} is the threshold of dorsiflexion angle.

In this study, we need to adjust the control parameters for different prosthesis users. But for each specific prosthesis user, the same parameters are adopted when the user walks in different conditions (at different speeds and on ramps of different inclination angles). Here, we choose the control parameters corresponding to the level ground walking at normal speed for all the walking conditions.

C. On-Board Adaptive Algorithm

In this study, an on-board adaptive algorithm is proposed to detect MDF timing. The core of this adaptive algorithm is to update the detection model automatically and continuously according to the detection result using the latest gait data in current walking condition. Hence, we can get a time-variant detection model based on the adaptive algorithm.

The adaptive algorithm is to use the IMU and ankle angle signals of prosthesis as the inputs and output the final detection result and update model continuously. In the adaptive algorithm, the angle signals of prosthetic ankle is used to label data and the preprocessed IMU signals are used as the input of detection and collected to update the training data set at the same time. The pseudo-code of the adaptive algorithm can be seen in Algorithm 1 in the Appendix Section (at the end of this article). The main procedures of the adaptive algorithm consist of three steps: 1) training data collecting and labeling; 2) model training based on training data set and real-time detection based on trained model; and 3) model updating.

1) Training Data Collecting and Labeling: In this study, signals of angle sensor and IMU are collected, and buffers are used to save the collected data with corresponding labels as the training data set. The goal of this study is to detect MDF

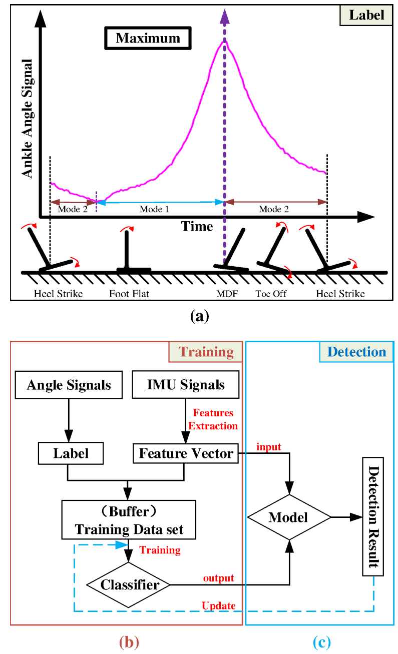

Fig. 2. Flowchart of designed on-board adaptive algorithm. (a) Data labeling based on ankle angle signals. (b) Model training (updating). (c) Real-time detection.

(maximum of ankle angle in each gait cycle) timing which can be labeled according to the angle signals of prosthetic ankle in each gait cycle. In Fig. 2(a), when one gait cycle ends, we can label the phase from timing corresponding to the minimum ankle angle to the timing corresponding to the maximum ankle angle as mode 1, and mode 2 is corresponding to the rest phase from the maximum ankle angle (timing) to the minimum ankle angle (timing). The transition timing from mode 1 to mode 2 is the real MDF timing.

2) On-Board Training and Real-Time Detection: For training and detection, some features of raw signals need to be extracted at first. Feature extracting is performed based on raw signals by a sliding window to acquire more valuable information, which can be seen in Fig. 2(b) and (c). The feature extracting method is used as follows. Raw IMU signals of eight variables (two angles, tri-axis acceleration, and tri-axis angular velocity) are collected by a sliding window (its length is 60 ms and the sliding increment is 10 ms) (the sample frequency is 100 Hz). Five time domain features are selected, which are shown as follows: average, standard deviation, minimum, maximum, and difference value of adjacent two elements. All features are pooled to be a feature vector $\boldsymbol{x}$, and the dimension of $\boldsymbol{x}$ is 40 (five features of each variables' signal and there are eight variables' signals in total). For model training/updating, feature vectors are buffered with their specific mode labels (mode 1 or mode 2) as a training data set. The detection model is generated based on the adaptive algorithm using training data set, as shown in Fig. 2(b).

In this study, support vector machine (SVM) algorithm is used to train model and detect MDF timing. We embedded LIBSVM [21] (a library for SVMs) into the control circuit of prosthesis to realize on-board training and real-time detection, which is an easy-to-use and efficient software for SVM

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classification and regression [21]. SVM is to construct an optimal hyperplane to separate the data belonging to different modes (labels) [22]. The hyperplane equation is as follows:

$$\boldsymbol{w} \cdot \boldsymbol{x} + b = 0 \tag{6}$$

where ω is the weight vector, b is the constant item (bias), and x is input vector (i.e., feature vector). To construct this hyperplane, we need to optimize the objective function, and the objective function is as follows:

$$\begin{aligned} &\min_{\boldsymbol{w},\boldsymbol{x}} \left(\frac{1}{2}\|\boldsymbol{w}\|^2 + C\left(\sum_{i=1}^{N} \xi_i\right)\right) \\ &\text{s.t. } y_i[\boldsymbol{w} * \boldsymbol{x_i} + b] \geq 1 - \xi_i \\ &\qquad \xi_i \geq 0, \quad i = 1, 2, \ldots, N \end{aligned} \tag{7}$$

where C is the penalty parameter (the default of C is 1) that represents penalty for misclassification, and its function is adjusting the confidence interval range. N is the number of training data samples, ξ_i is the relaxation factor corresponding to the i_{th} training data sample ($\boldsymbol{x_i}$). y_i ($y_i = 1$ or -1) is the label corresponding to $\boldsymbol{x_i}$.

In this study, the radial basis function (RBF) is chosen as the kernel function of SVM to realize on-board training. It is shown as follows:

$$K(\boldsymbol{x_i}, \boldsymbol{x}) = \exp\left(-\gamma \|\boldsymbol{x_i} - \boldsymbol{x}\|^2\right) \tag{8}$$

where $K(\boldsymbol{x_i}, \boldsymbol{x})$ is the kernel function of SVM, and γ is a coefficient that determines the distribution of data mapped to a new feature space and its function is adjusting the effect of each sample on the classification hyperplane ($\gamma = 1/n$ (default), where n is the feature vector's dimension). When finish optimizing the objective function, we can get the discriminant function as follows:

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\boldsymbol{w}^* \cdot \boldsymbol{x} + b^*\right) = \operatorname{sgn}\left(\sum_{i=1}^{M} \alpha_i y_i K(\boldsymbol{x_i}, \boldsymbol{x}) + b^*\right) \tag{9}$$

where sgn is the sign function, $\boldsymbol{w}^*$ is the optimized weight vector, b^* is the optimized bias, M is the number of total support vectors, $\boldsymbol{x_i}$ is the ith support vector, $\boldsymbol{x}$ is input feature vector, α_i is the coefficient corresponding to support vector $\boldsymbol{x_i}$, and y_i is the label corresponding to support vector $\boldsymbol{x_i}$.

For real-time detection, IMU signals will be preprocessed to generate feature vectors. The feature vector streams will be fed into the model, and the continuous detection results will be output, which can be seen in Fig. 2(c). The preliminary detection result for each input (feature vector) is mode 1 or mode 2. By discriminating the transition timing from mode 1 to mode 2, we can get the detected MDF timing.

3) Model Updating: Detection Model can be updated automatically according to the detection result, as shown in Fig. 2(b) and (c). In this study, data labeling is automatic as soon as one gait cycle ends. Therefore, the training data set is also updated automatically gait cycle by gait cycle. When an update is needed, the new model will be trained based on the updated training data set, and the real-time detection based on updated model will be performed then. During the model updating period, the detection is executed based on the existing model and then switches to updated model as soon as model updating is finished.

TABLE I
INFORMATION OF THE THREE PARTICIPANTS WITH TRANSTIBIAL AMPUTATIONS

	Gender	Age	Weight (kg)	Height (cm)	Years post-amputation	The amputation side
Participant 1	Male	52	70	170	17	Left
Participant 2	Male	56	81	170	10	Left
Participant 3	Male	30	72	171	9	Right

TABLE II
DESIGNED EXPERIMENTS

	Speed/Inclination				
Speed Experiment		S^a/0°	N^b/0°	F^c/0°	
Ramp Experiment	N/10°	N/5°	N/0°	N/-5°	N/-10°

[a] S denotes slow speed. [b] N denotes normal speed. [c] F denotes fast speed.

D. Experimental Protocol

Three persons with transtibial amputations were recruited in this study as participants, and the detailed information of participants are listed in Table I. All participants have signed written informed consents and the study has been approved by the Local Ethics Committee of Peking University (Permission No.: #2018-06-02). In this study, each participant would do some exercises before the experiments to adapt to the robotic transtibial prosthesis.

Two formal experiments were conducted to validate the adaptive algorithm for MDF timing detection, as shown in Table II. The first experiment was to detect MDF timing at different walking speeds (speed experiment). Three participants were asked to walk on the treadmill at their self-selected speeds (slow, normal, and fast) to train model and then the real-time MDF timing detection was conducted. The second experiment was to detect MDF timing on different ramps (ramp experiment). All participants walked on the treadmill with different inclination angles (10°, 5°, 0°, −5°, and −10°) (as ramps) at their normal walking speeds. Inclination angles (10° and 5°) were corresponding to ramp ascending, inclination angle (0°) was corresponding to level ground walking and inclination angles (−5° and −10°) were corresponding to ramp descending.

In this study, each participant walked for about 2 min for each walking conditions, from 0 m/s, accelerated to the steady speed and kept for 1.5 min and slowed down. During this period, data were collected as training data set to training model and then continuous 20 gait cycles were analyzed (real-time detection and model updating) for each condition.

E. Off-Line Threshold Detection for Comparison

Threshold method has been used in MDF timing detection [1], [10], [16]. To compare with the proposed adaptive algorithm, we conducted off-line analysis for MDF timing detection based on threshold decision method. The decision

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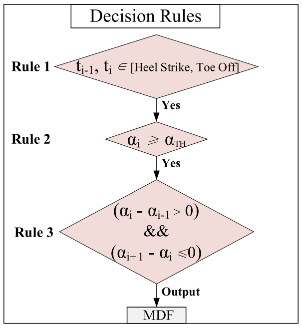

Fig. 3. Rules of threshold decision method. t_i denotes the ith sampling instant. α_i (obtained by angle sensor) denotes the angle of prosthetic ankle corresponding to t_i. α_{TH} denotes the set angle threshold.

rules of threshold method are shown in Fig. 3. In Fig. 3, there are three decision rules for MDF timing detection based on raw ankle angle signals. The first rule is used to ensure that MDF timing is detected just in the stance phase, since MDF timing occurs in the stance phase [10]. The second rule is used to narrow the range to decrease false detection by comparing with the set angle threshold (i.e., α_{TH}). When the angle α_i is bigger than α_{TH}, the third rule is used to detect MDF timing by detecting the change of sign of the difference signal of angle. MDF timing is corresponding to the change timing of sign of angle differential signal. In the process of MDF timing detection in each gait cycle, the decision rules start to run in heel strike and stop running once MDF timing is detected in the current gait cycle, which can ensure that just one MDF timing is detected in each gait cycle.

According to the manner to set the α_{TH}, the threshold decision method can be divided into: 1) the nonadaptive and 2) adaptive threshold decision methods. As to the non-adaptive (fixed) threshold decision method, the set thresholds are fixed all the time for different walking conditions. The threshold (α_{TH}) is set artificially under the higher detection accuracy premise and it varies with different walking conditions and different participants. Besides, we also explore an adaptive threshold decision method to conduct MDF timing detection. The adaptive threshold decision method is to detect the local maximum of the recorded ankle angle trajectory of the previous gait cycle, set the angle threshold (α_{TH}) as a percentage of the local maximum, and adjust for the current gait cycle.

F. System Evaluation

The performances of adaptive algorithm for MDF timing detection are important for prosthesis. Three metrics are adopted to evaluate the performances: response time (including training and detecting), detection accuracy, and detection delay.

1) Model Training/Updating and Detection Time: In this study, each frame of data is collected and processed during the current gait cycle. As soon as one gait cycle ends, we can get the angle curve trajectory of the whole gait cycle and label each frame of processed data (feature vector) in this gait cycle. Then the training data set is updated by replacing the earliest gait cycle's data with the latest gait cycle's data. The adaptive algorithm system includes model training/updating and real-time detection. The process for detection model training is that training data set is input into the adaptive algorithm and then outputs detection model. Model updating is practically the retraining of the model. Each detection process is that a feature vectors is fed into the model and the recognition result is output. The elapsed time of training/updating process and detection process are defined as training/updating and detection time.

2) Detection Accuracy: The accuracy of detection for MDF timing directly reflects the performance of the adaptive algorithm. In each gait cycle, the MDF timing occurs just once. If more or less than one MDF timing is detected in each gait cycle, it means it is a false detection. Besides, if the MDF timing is detected 50 ms (five sample intervals) earlier or later than the real MDF timing (labeled by the angle signals of prosthetic ankle), it is also considered as a false detection. The 50 ms can be viewed as a tolerance of error.

3) Detection Delay: When MDF timing is detected correctly, a delay may exist between the detected MDF timing and the real MDF timing (labeled by the angle signals of prosthetic ankle). The delay time T_d is calculated by the following equation:

$$T_d = t_d - t_l \tag{10}$$

where t_l is the real MDF timing labeled by angle signals of prosthetic ankle and t_d is the detected MDF timing. Positive T_d represents that the MDF timing is detected behind the real MDF timing and the negative T_d denotes the MDF timing is detected before the real MDF timing.

T_d varies from one participant to another participant and also from one gait cycle to another gait cycle, and the duration (time length) of each gait cycle also varies. Therefore, a normalized metric [delay proportion to gait cycle (P_d)] is used to evaluate the detection delay performance. P_d is calculated as follows:

$$P_d = \frac{T_d}{T_c} \times 100\% \tag{11}$$

where T_c is the duration of one gait cycle and T_d is the delay time of detection. The meanings of the positive or negative signs of P_d are the same as the signs of T_d.

III. Results

A. Angle Signals of Prosthetic Ankle

Participants were asked to walk at different speeds and on ramps of different inclination angles. During the experiments, angle signals of prosthetic ankle were recorded and the normalized angle curves were shown in Fig. 4(a)–(c) and (d)–(f). Angle signals of prosthetic ankle for the three participants were different from each other. Compared with the MDF angle, we cared more about the MDF timing in this study. There existed a lot of differences in MDF timing when participants walked at different speeds, as shown in Fig. 4(a)–(c) and on different ramps, as shown in Fig. 4(e)–(f).

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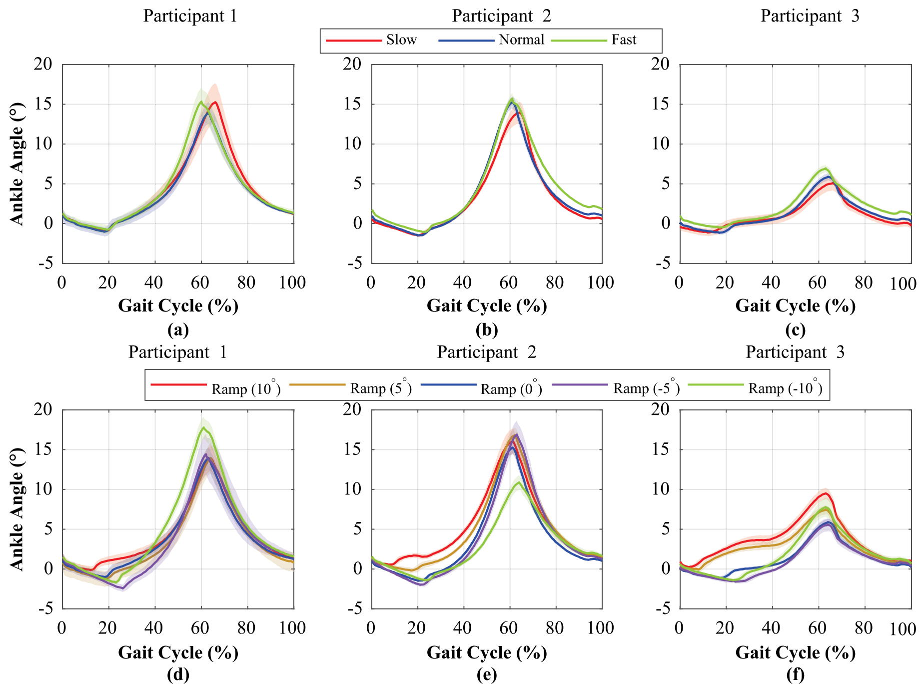

Fig. 4. Normalized angle signals of prosthetic ankle in one gait cycle at different speeds and on different ramps. (a–(c) Normalized ankle angle signals at different speeds (slow, normal, and fast) for level ground walking, corresponding to participant 1–3. (d)–(f) Normalized ankle angle signals on different ramps (inclination angles: 10°, 5°, 0°, −5°, and −10°) at normal walking speeds, corresponding to participant 1–3. The colorful solid lines denote the means and the shadow areas denote standard deviations. The gait cycle starts from heel strike, then to toe off and ends at next heel strike.

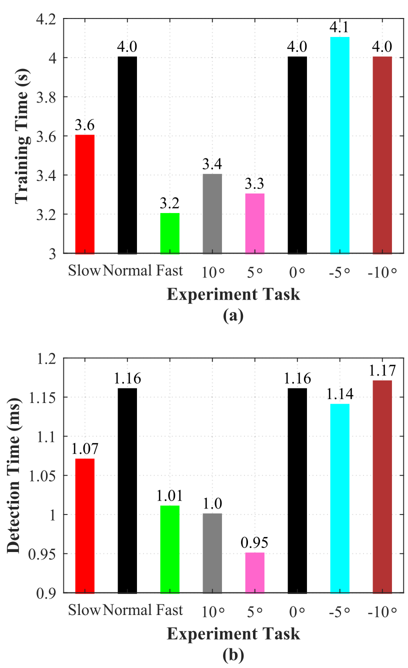

Fig. 5. Training and detection time of adaptive algorithm for MDF timing detection. (a) Training time. (b) Detection time. The bars of different colors denote different walking conditions and the values on the bars denote the training time [in (a)] and detection time [in (b)].

B. Model Training/Updating and Detection Time

Response time were comprised of model training/updating time and detection time, and the results were shown in Fig. 5. The training time was related with the size of training data set. In this study, continuous 20 gait cycles' data were collected as training data set, namely, the number of sample was N ($N = \sum_{i=1}^{20} n_i$, n_i denotes the sample number of the i_{th} gait cycle). Five features of eight variables of IMU were extracted and then formed a 1×40 feature vector. The training data set consisted of N feature vectors, and its size were $N \times 40$. For MDF timing detection, the dimensions of each input (feature vector) was 1×40.

For walking at slow, normal, and fast speeds, the mean model training time for the three participants were 3.6, 4.0, and 3.2 s, and the corresponding detection time were 1.07, 1.16, and 1.01 ms, as shown in Fig. 5(a) and (b), respectively. When participants walked on ramps of different inclination angles (10°, 5°, 0°, −5°, and −10°) at normal speeds, the mean model training time were 3.3, 3.4, 4.0, 4.1, and 4.0 s, and the corresponding detection time were 1.0, 0.95, 1.16, 1.14, and 1.17 ms, as shown in Fig. 5(a) and (b), respectively. Model updating time was corresponding to model training time, since model updating was practically the model retraining. The maximum training time was 4.1 s (corresponding to ramp of −5°) and the minimum training time was 3.2 s (corresponding to fast speed). The detection time ranged from 0.95 ms (minimum) (corresponding to ramp of 5°) to 1.17 ms (maximum) (corresponding to ramp of −10°).

C. Real-Time Detection Results

1) Detection Accuracy: In each gait cycle, the right detection was that just one MDF timing was detected in each gait cycle within 50-ms time tolerance relative to the real MDF timing (labeled by angle signals of prosthetic ankle). The detection results could be seen in Table III. In real-time detection experiments for participant 1 and participant 3, all the MDF timings were detected correctly (i.e., no false detection), no matter participants walked at different speeds

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TABLE III
FALSE DETECTION FOR THE THREE PARTICIPANTS

	Speed			Inclination				
	Slow	Normal	Fast	10°	5°	0° [a]	-5°	-10°
Participant 1	0	0	0	0	0	0	0	0
Participant 2	0	5.0%	0	0	0	5.0%	0	0
Participant 3	0	0	0	0	0	0	0	0
Mean	0	1.67%	0	0	0	1.67%	0	0

[a] Ramp with 0° inclination is practically the level ground.

or on different ramps. For participant 2, there existed false detection (5.0%) for MDF timing in level ground walking at normal speed. For the other conditions, the algorithm could achieve 100% detection accuracy. The mean false detection was 1.67% for level ground walking at normal speed for the three participants.

2) Detection Delay: The detection delay time (T_d) and its corresponding proportion (P_d) to gait cycle could be seen in Table IV. The delay time were 0.23 ± 2.61, 18.27 ± 4.07, 7.50 ± 1.44, 10.60 ± 1.87, 10.30 ± 4.66, 18.27 ± 4.07, 10.27 ± 6.00, and 15.63 ± 0.95, corresponding to walking at different speeds and on different ramps. The delay proportions for walking at slow, normal and fast speeds were 0.46% ± 0.19%, 1.23% ± 0.20%, and 0.60% ± 0.11%, which illustrated the detected MDF timing were behind the real MDF timing (delay proportions were positive). The delay proportions for walking on ramps of different inclination angles (10°, 5°, 0°, −5°, and −10°) were 0.76% ± 0.13%, 0.77% ± 0.35%, 1.23% ± 0.20%, 0.78% ± 0.49%, and 1.18% ± 0.07%, which also illustrated the detected MDF timing was behind the real MDF timing (delay proportions were positive). The maximum delay proportion was 1.23% for walking at normal speed and on ramp of 0°. The minimum delay proportion was 0.46% for walking at slow speed.

D. Off-Line Detection Results Based on Threshold Decision Method

1) Results Based on Nonadaptive (Fixed) Threshold Decision Method: To compare with the proposed adaptive method, off-line detection was conducted for MDF timing based on threshold decision method. For the nonadaptive (fixed) threshold decision method, the set angle threshold (α_{TH}) and detection result were listed in Table V. The α_{TH} varied with different walking conditions and depended on participants themselves, as shown in the bracket of Table V. As mentioned, if MDF timing was detected 50 ms (five sample intervals) earlier or later than the real MDF timing or no MDF event was detected, it was a false detection. For participant 1, the maximum false detection was 20.0% for walking on ramp of −5°, and the minimum was 0 (i.e., 100% detection accuracy) for level ground walking at normal speed. For participant 2, the maximum false detection was 20.0% (ramp of −5°), and the minimum was 0 for level ground walking at slow speed. For participant 3, the maximum false detection was 15.0% corresponding to walking on ramps of 10° and −5°, and the minimum was 5.0%. The mean false detection was listed at the end row of Table V, and the maximum mean false detection was 10.0% (ramp of 5°) and the minimum was 5.0% (walking at slow and fast speeds, respectively).

Using the nonadaptive threshold decision method, there existed positive and negative delay time between the detected MDF timing and real MDF timing, as shown in Table VI. Delay time ranged from −22.37 ± 7.15 ms (at slow speed) to 3.05 ± 2.10 ms (at fast speed), and the corresponding proportions to gait cycle ranged from −1.34% ± 0.47% to 0.23% ± 0.16%. For walking at normal speed on level ground, the delay proportion to gait cycle was −0.12%, which was the minimum (no sign into consideration). The maximum delay proportion to gait cycle (no sign into consideration) was −1.34%, corresponding to walking at slow speed. The negative sign represented that the detected MDF timing was before the real MDF timing.

2) Results Based on Adaptive Threshold Decision Method: Using the adaptive threshold method, we chose 70%, 80%, and 90% of the local maximum as the thresholds for all participants in different walking conditions, respectively. The analysis results based on the adaptive threshold method could be seen in Table VII. When the threshold was set as 70% of the local maximum, the mean false detections of three participants were 15.0%, 13.3%, and 8.3%, corresponding to walking at slow, normal and fast speeds, and they were 16.7%, 16.7%, 13.3%, 20.0%, and 15.0%, corresponding to different ramps (10°, 5°, 0°, −5°, and −10°). When the thresholds were set as 80% and 90% of the local maximum, there still existed false detections, as shown in Table VII.

The detection delay and proportion to gait cycle were listed in Table VIII. There existed positive and negative delay time between the detected MDF timing and real MDF timing. When the percentage was 70%, the delay time ranged from −26.90 ± 9.31 to 2.45 ± 2.31 ms, and it ranged from −27.16 ± 10.13 to 3.29 ± 1.61 ms and −25.92 ± 7.58 to 5.72 ± 1.28 ms, corresponding to different percentages (80% and 90%), as shown in Table VIII. When the angle thresholds were set as different percentages of the local maximum, the proportions varied a lot. The proportion to gait cycle varied from −1.83% ± 0.93% to 0.18% ± 0.18%, from −1.62% ± 0.65% to 0.12% ± 0.21%, from −1.54% ± 0.47% to 0.43% ± 0.09%, corresponding to the percentages (70%, 80%, and 90%). When the angle threshold was set as 90% of the local maximum, this study could achieve 0.18% ± 5.24% [at normal speed and on ramp (0°)] and the proportion to gait cycle was 0.00% ± 0.38%, which represented there existed little detection delay between the detected MDF timing and real MDF timing.

IV. DISCUSSION

MDF timing plays an important role in prosthesis control [10]–[12], [16]. In different walking conditions (such as at different speeds or on different ramps) and for different robotic prosthesis users, MDF timings are different. Therefore, it is meaningful to realize adaptive detection for MDF timing. Threshold decision method directly from angle sensor of prosthetic ankle has low adaptation for MDF timing detection.

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TABLE IV

DELAY TIME (T_d) AND PROPORTION TO GAIT CYCLE (P_d) FOR MDF TIMING DETECTION BASED ON THE ADAPTIVE ALGORITHM

	Speed			Inclination				
	Slow	Normal	Fast	10°	5°	0°	-5°	-10°
T_d (ms)	7.23 ± 2.61	18.27 ± 4.07	7.50 ± 1.44	10.60 ± 1.87	10.30 ± 4.66	18.27 ± 4.07	10.27 ± 6.00	15.63 ± 0.95
P_d (%)	0.46 ± 0.19	1.23 ± 0.20	0.60 ± 0.11	0.76 ± 0.13	0.77 ± 0.35	1.23± 0.20	0.78 ± 0.49	1.18 ± 0.07

TABLE V

FALSE DETECTION AND SET ANGLE THRESHOLD (α_{TH}) BASED ON THE NONADAPTIVE THRESHOLD DECISION METHOD

	Speed			Inclination				
	Slow	Normal	Fast	10°	5°	0°	-5°	-10°
Participant 1	10.0% (11.0°)[a]	0.0% (11.5°)	5.0% (12.5°)	5.0% (10.0°)	15.0% (9.0°)	0.0% (11.5°)	20.0% (11.3°)	5.0% (15.0°)
Participant 2	0.0% (11.0°)	15.0% (13.0°)	5.0% (12.5°)	0.0% (13.0°)	5.0% (14.0°)	15.0% (13.0°)	20.0% (13.8°)	5.0% (9.5°)
Participant 3	5.0% (4.5°)	5.0% (4.5°)	5.0% (5.5°)	15.0% (8.0°)	10.0% (6.0°)	5.0% (4.5°)	15.0% (4.0°)	10.0% (5.5°)
Mean	5.0%	6.7%	5.0%	6.7%	10.0%	6.7%	18.3%	6.7%

[a] The content in the bracket is the value of set α_{TH}.

TABLE VI

DELAY TIME (T_d) AND PROPORTION TO GAIT CYCLE (P_d) FOR MDF TIMING DETECTION BASED ON THE NONADAPTIVE THRESHOLD DECISION METHOD

	Speed			Inclination				
	Slow	Normal	Fast	10°	5°	0°	-5°	-10°
T_d (ms)	-22.37 ± 7.15	-1.80 ± 5.92	3.05 ± 2.10	-6.66 ± 4.42	-9.23 ± 5.50	-1.80 ± 5.92	-9.14 ± 5.20	-1.95 ± 6.43
P_d (%)	-1.34 ± 0.47	-0.12 ± 0.40	0.23 ± 0.16	-0.48 ± 0.32	-0.69 ± 0.43	-0.12 ± 0.40	-0.69 ± 0.44	-0.17 ± 0.50

TABLE VII

(MEAN) FALSE DETECTION BASED ON THE ADAPTIVE THRESHOLD DECISION METHOD

	Speed			Inclination				
Percentage[a]	Slow	Normal	Fast	10°	5°	0°	-5°	-10°
70%	15.0%	13.3%	8.3%	16.7%	16.7%	13.3%	20.0%	15.0%
80%	11.7%	8.3%	1.7%	15.0%	18.3%	8.3%	8.3%	11.7%
90%	21.7%	8.3%	3.3%	11.7%	13.3%	8.3%	11.7%	11.7%

[a] The threshold is set as a percentage of the local maximum.

TABLE VIII

DELAY TIME (T_d) AND PROPORTION TO GAIT CYCLE (P_d) FOR MDF TIMING DETECTION BASED ON THE ADAPTIVE THRESHOLD DECISION METHOD

		Speed			Inclination				
Percentage		Slow	Normal	Fast	10°	5°	0°	-5°	-10°
70%	T_d (ms)	-26.90 ± 9.31	-8.20 ± 6.53	2.45 ± 2.31	-25.77 ± 13.29	-24.72 ± 11.03	-8.20 ± 6.53	-14.25 ± 4.25	-3.38 ± 4.23
	P_d (%)	-1.60 ± 0.58	-0.56 ± 0.44	0.18 ± 0.18	-1.83 ± 0.93	-1.81 ± 0.83	-0.56 ± 0.44	-1.02 ± 0.38	-0.27 ± 0.33
80%	T_d (ms)	-27.16 ± 10.13	-6.20 ± 6.08	3.29 ± 1.61	-13.17 ± 5.84	-17.74 ± 9.46	-6.20 ± 6.08	-8.32 ± 4.63	1.70 ± 2.74
	P_d (%)	-1.62 ± 0.65	-0.40 ± 0.39	0.26 ± 0.12	-0.95 ± 0.43	-1.32 ± 0.74	-0.40 ± 0.39	-0.60 ± 0.37	0.12 ± 0.21
90%	T_d (ms)	-25.92 ± 7.58	0.18 ± 5.24	4.60 ± 1.78	-6.20 ± 8.17	-10.77 ± 8.88	0.18 ± 5.24	3.40 ± 4.51	5.72 ± 1.28
	P_d (%)	-1.54 ± 0.47	0.00 ± 0.38	0.36 ± 0.13	-0.44 ± 0.59	-0.81 ± 0.68	0.00 ± 0.38	0.19 ± 0.32	0.43 ± 0.09

To solve this problem, an on-board adaptive algorithm based on the idea of supervised pattern recognition for MDF timing detection is proposed in this study. The core of adaptive algorithm is to use the latest gait data in current walking condition to update detection model according to the results to detect MDF timing. The detection model can vary as time to fit different prosthesis users walking in different conditions, which shows its auto-customized features for prosthesis users

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as walking conditions change. The corresponding experiments are conducted on three participants wearing robotic transtibial prostheses. The IMU and ankle angle sensor of prosthesis are used to train model and detect MDF timing based on the adaptive algorithm.

Feature selection is important in pattern recognition. In this study, we have selected five time domain features to extract the features of IMU signals, which are average, standard deviation, minimum, maximum, and difference value of adjacent two elements. These time domain features have been validated effectively in some previous studies [23], [28]. Both Huang *et al.* [23] and Zheng and Wang [25] in their offline and online locomotion mode recognition studies have selected four features (average, standard deviation, minimum, and maximum) to extract the IMU signals. In our previous study [24], the same five features have also been selected to extract the IMU signals and shown good effects in real-time recognition.

In this study, the detection for MDF timing is based on SVM algorithm, and we have selected the RBF as the kernel function of SVM, since it has been widely used in lower-limb locomotion recognition [23], [24]. Zheng and Wang [25] have conducted lower-limb locomotion mode recognition based on robotic prosthesis and analyzed the effects of different kernel functions of SVM. They have concluded that RBF shows better recognition performance than linear kernel function. Huang *et al.* [23] have also used the RBF as the kernel function of SVM in lower-limb locomotion mode recognition and got good recognition performance [26]. Additionally, the RBF is usually a reasonable first choice for general users as it can handle the nonlinear relation between class labels and attributes [27]. The main parameters of SVM based on RBF are C and γ, as shown in (7) and (8). C is the penalty parameter represents penalty for misclassification and its function is adjusting the confidence interval range. γ is the coefficient and its function is adjusting the effect of each sample on the classification hyperplane. In this study, the defaults of parameters are: $C = 1$ and $\gamma = 1/n$ [where n is the feature vector's dimension ($n = 40$)]. We have not conducted parameters tuning in this study, and the two parameters (C and γ) are kept constant for all the participants in different walking conditions. Based on these parameters, this study has achieved satisfactory results. In addition, using the default parameters requiring no experimenter's tuning is beneficial to adaptive detection for different prosthesis users in different walking conditions.

A. Real-Time Detection Performance of Adaptive Algorithm

The response performances of the on-board adaptive algorithm system consist of model training/updating time and detection time. The short training time means a good response performance. Spanias *et al.* [28] have studied the online locomotion modes recognition, and their forward predictors (i.e., models) are updated 125 times within a 10-min period (i.e., 4.8 s per time). Our study for MDF timing detection has achieved comparable response performance (3.2–4.0 s) with their study. The detection time are from 0.95 to 1.17 ms corresponding to different speeds and ramps. In this study, the sliding window increment is 10 ms, which means that the detection must be finished within 10 ms [29]. The maximum detection time of the study is 1.17 ms that is less than 10 ms (the proportion is just 11.7%), which meets the requirement.

MDF timings are different in different walking conditions and for different prosthesis users, as shown in Fig. 4. The detection results show that there is false detection for participant 2 walking at normal speed. Except this, all MDF timings can be detected correctly for the three participants based on the adaptive algorithm, as shown in Table III. There exists delay between the detected MDF timing and the real MDF timing, as seen in Table IV. All the delay time are positive value, which denotes the detected MDF timing is behind the real MDF timing (labeled by the ankle angle in each gait cycle). The maximum delay time is 18.27 ± 4.07 and the proportion to one gait cycle $1.23\% \pm 0.20\%$, which shows it matters little to each gait cycle. Bejarano *et al.* [19] have conducted gait events detection (not for MDF) and the detection delay time of their study are below 14 and 31 ms for healthy and stroke people. Therefore, our study based on proposed adaptive algorithm has achieved comparable and even better performances than their study.

B. Off-Line Threshold Decision Method

Threshold decision method has been used to detect MDF timing in previous studies [10], [16]. Here, to compare with the proposed method, we have also conducted an off-line analysis for MDF timing detection based on the nonadaptive (fixed) and adaptive threshold methods. It is the first consideration to detect MDF timing directly according to the raw ankle angle signals. This study has designed a series of decision rules (as shown in Fig. 3) to conduct MDF timing detection based on the raw angle signals of prosthetic ankle. For the nonadaptive threshold decision method, the α_{TH} is set artificially and fixed during walking. For the adaptive threshold decision method, the threshold (α_{TH}) is set as a percentage of the local maximum, and adjust for the current gait cycle. One important issue is how to set the percentage, and there is no good method in current studies to address this issue. In this study, we have tried to choose 70%, 80%, and 90% of the local maximum as the thresholds for all participants in different walking conditions to detect MDF timing. We can see from Table VII that the adaptive threshold decision methods performance is even worse than the nonadaptive (fixed) threshold performance, importantly in the "Normal" and "0°" conditions, which have shown that detection accuracy is related with the thresholds and the threshold set methods. The adaptive threshold decision method is to detect the local maxima of the recorded ankle angle trajectory of the previous gait cycle, set the angle threshold as a percentage of the local maxima, and adjust for the current gait cycle. The percentage is set uniformly for all the participants and for different walking conditions, which cannot guarantee a better performance. Besides, in our study, we just select three discrete percentages (70%, 80%, and 90%) to study the detection performance. It may require an elaborate percentage adjusting to acquire better detection performance. While for the nonadaptive threshold decision method, the threshold is set according to each participant and

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different walking conditions, hence we have acquired better detection performance than the adaptive threshold decision method in some walking conditions.

Both the nonadaptive and adaptive threshold methods can get false detections, as shown in Tables V and VII. While the proposed adaptive algorithm based on pattern recognition in this study has less false detection, as shown in Table III. Using the nonadaptive and adaptive threshold methods, this study can get positive or negative delay time for different walking conditions, which means the detected MDF timing is before or behind the real MDF timing. In addition, different threshold can cause the different delay time for the same walking condition, as shown in Tables VI and VIII. The detection delay is related with the set thresholds. So, how to set thresholds for different walking conditions and prosthesis users need to be carefully addressed. When using adaptive algorithm, this study can get positive delay time for all the walking conditions. Namely, the detected MDF timing is behind the real MDF timing, which is be related with SVM algorithm itself. Except the positive and negative signs of detection delay, from the delay time value (no signs in consideration) in Tables IV, VI, and VIII, we can see that the adaptive algorithm can be achieved comparable detection delay time with the nonadaptive and adaptive threshold methods. Besides, the adaptive algorithm donot need to set or tune any parameters artificially in advance, which decreases the dependence on experimenters.

C. Comparison With Other Studies

There are quite few studies about the MDF timing detection with adaptation. Some studies concerning MDF timing detection often utilize the threshold decision method. Shultz *et al.* [1] and Au *et al.* [10] have conducted MDF timing detection from the angle signals of prosthetic ankle based on threshold decision rules. Feng and Wang [16] have also conducted MDF timing detection using ankle angle and interaction force information together by setting different angle thresholds and force thresholds artificially. All these studies cannot get good results in detecting MDF timing. In addition, the set of threshold decision rules is artificial and the thresholds are always fixed, which is simple but without adaptation for MDF timing detection. Bejarano *et al.* [19] have explored an adaptive threshold rules to detect some gait events (not for MDF), such as initial contact, end contact, mid swing. Our study show better detection delay performance than their study. In addition, their study still requires some off-line operations to get some parameter values, and lacks of adaptation for different people. Their adaptive threshold method still needs further exploration. Compared with the existing studies based on fixed threshold decision method [1], [10] or adaptive threshold method [19], our study adopts supervised pattern recognition method and designs adaptive algorithm to overcome these disadvantages and gets good adaptation for MDF timing detection in different walking conditions and for different prosthesis users.

In addition to the mentioned adaptive detection for MDF timing in different walking conditions and for prosthesis users, the adaptive algorithm also show its adaptation and application prospects in some other aspects. For the robotic prosthesis, the users will wear prosthesis for long time and often need to don-off and don prosthesis in daily activities. Fixed detection model will cause detection performance decline facing these variations. The adaptive algorithm can update model according the latest data automatically and then conduct the detection, which can adapt to these conditions (long time wearing or don-off and don prosthesis frequently).

Algorithm 1 Adaptive Algorithm for MDF Timing Detection

Input: The ankle angle of prosthesis, $Angle$;
The IMUs Signals, $\boldsymbol{X}$;
Output: Detection result, Res;
while 1 **do**
  Conduct preprocess (feature extraction) for $\boldsymbol{X}$ and get feature vector $\boldsymbol{Y}$;
    $\boldsymbol{Y} = P(\boldsymbol{X})$;
  if exist Model $\boldsymbol{F}$ **then**
    $Res = \boldsymbol{F}(\boldsymbol{Y})$;
  end if
  add feature vector $\boldsymbol{Y}$ into a buffer $\boldsymbol{Buf1}$ and add ankle angle $Angle$ into a buffer $\boldsymbol{Buf2}$;
    $\boldsymbol{Buf1} = [\boldsymbol{Buf1}; Y]$;
    $\boldsymbol{Buf2} = [\boldsymbol{Buf2}; Angle]$;
  if finish the data collection of one whole gait cycle in $\boldsymbol{Buf1}$ and $\boldsymbol{Buf2}$ **then**
    find the positions (i_{max} and i_{min}) of the maximum and minimum angle of $\boldsymbol{Buf2}$
      $i_{max} = \text{position}(\max(\boldsymbol{Buf2}))$;
      $i_{min} = \text{position}(\min(\boldsymbol{Buf2}))$;
    for each $i \in [1, n]$ and n is the length of $\boldsymbol{Buf2}$ **do**
      if $i > i_{min}$ and $i < i_{max}$ **then**
        $\boldsymbol{Label}[i] = 1$;
      else
        $\boldsymbol{Label}[i] = 2$;
      end if
    end for
    add $\boldsymbol{Buf1}$ and $\boldsymbol{Label}$ into training data set $\boldsymbol{D}$ to update training data set
      $\boldsymbol{D} = [\boldsymbol{D}; \boldsymbol{Buf1}; \boldsymbol{Label}]$;
    clear some oldest data in $\boldsymbol{D}$
    clear the two buffers $\boldsymbol{Buf1}$ and $\boldsymbol{Buf2}$
  end if
  if no model ($\boldsymbol{F}$) exists or need to update model ($\boldsymbol{F}$) **then**
    Conduct model training based on training data set $\boldsymbol{D}$ using SVM algorithm;
      $\boldsymbol{F} = SVM(\boldsymbol{D})$;
  end if
end while

D. Limitations

Though the proposed adaptive algorithm performs good performance, this study still needs further improvements. First, the detection accuracy may be improved with shorter delay.

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Second, our study focused mainly on the adaptive detection for MDF timing. We will conduct prosthesis control based on the proposed MDF detection algorithm. In addition, most of the recent studies for gait events detection are conducted in structured environment. In the future, we will conduct further study in outdoor environment to improve the assistance for prosthesis users.

V. Conclusion

This article puts forward an on-board adaptive algorithm to detect the MDF timing based on IMU and ankle angle signals of robotic transtibial prosthesis. Real-time detection experiments are conducted based on the adaptive algorithm at different walking speeds (slow, normal, and fast), on different ramps (10°, 5°, 0°, −5°, and −10°) and for different prosthesis users. (Three transtibial amputees participated in this study.) In real-time detection, there is false detection (1.67%) in the condition (level ground walking at normal speed). Except this, all MDF timings can be detected correctly. The proposed adaptive algorithm has satisfactory adaptation for MDF timing detection in different walking conditions (at different speeds and on different ramps) and for different users, which is helpful to prosthetic control in the future.

Appendix

The detailed implementation (pseudo-code) of the adaptive algorithm for MDF timing detection is presented in Algorithm 1.

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References

[1] A. H. Shultz, B. E. Lawson, and M. Goldfarb, "Variable cadence walking and ground adaptive standing with a powered ankle prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 4, pp. 495–505, Apr. 2016.

[2] Q. Wang, K. Yuan, J. Zhu, and L. Wang, "Walk the walk: A lightweight active transtibial prosthesis," *IEEE Robot. Autom. Mag.*, vol. 22, no. 4, pp. 80–89, Dec. 2015.

[3] T. Lenzi, M. Cempini, L. J. Hargrove, and T. A. Kuiken, "Design, development, and validation of a lightweight nonbackdrivable robotic ankle prosthesis," *IEEE/ASME Trans. Mechatronics*, vol. 24, no. 2, pp. 471–482, Apr. 2019.

[4] H. Zhao, J. Horn, J. Reher, V. Paredes, and A. D. Ames, "Multicontact locomotion on transfemoral prostheses via hybrid system models and optimization-based control," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 502–513, Apr. 2016.

[5] S. Culver, H. Bartlett, A. Shultz, and M. Goldfarb, "A stair ascent and descent controller for a powered ankle prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 5, pp. 993–1002, May 2018.

[6] S. Au, M. Berniker, and H. Herr, "Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits," *Neural Netw.*, vol. 21, no. 4, pp. 654–666, May 2008.

[7] M. Grimmer *et al.*, "A powered prosthetic ankle joint for walking and running," *Biomed. Eng. OnLine*, vol. 15, no. S3, p. 141, Dec. 2016.

[8] M. R. Tucker *et al.*, "Control strategies for active lower extremity prosthetics and orthotics: A review," *J. Neuroeng. Rehabil.*, vol. 12, no. 1, pp. 1–29, Dec. 2015.

[9] K. Yuan, Q. Wang, and L. Wang, "Energy-efficient braking torque control of robotic transtibial prosthesis," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 1, pp. 149–160, Feb. 2017.

[10] S. K. Au, J. Weber, and H. Herr, "Powered ankle–foot prosthesis improves walking metabolic economy," *IEEE Trans. Robot.*, vol. 25, no. 1, pp. 51–66, Feb. 2009.

[11] M. Palmer, "Sagittal plane characterization of normal human ankle function across a range of walking gait speeds," M.S. thesis Dept. Mech. Eng., Massachusetts Inst. Technol., Boston, MA, USA, 2002.

[12] D. H. Gates, "Characterizing ankle function during stair ascent, descent, and level walking for ankle prosthesis and orthosis design," M.S. thesis, Dept. Biomed. Eng., Boston Univ., Boston, MA, USA, 2004.

[13] A. Hansen *et al.*, "The human ankle during walking: Implications for design of biomimetic ankle prostheses," *J. Biomech.*, vol. 37, no. 10, pp. 1467–1474, 2004.

[14] A. L. Hof, B. A. Geelen, and J. W. Van Den Berg, "Calf muscle moment, work and efficiency in level walking; role of series elasticity," *J. Biomech.*, vol. 16, no. 7, pp. 523–537, 1983.

[15] C. H. Soo and J. M. Donelan, "Coordination of push-off and collision determine the mechanical work of step-to-step transitions when isolated from human walking," *Gait Posture*, vol. 35, no. 2, pp. 292–297, Feb. 2012.

[16] Y. Feng and Q. Wang, "Combining push-off power and nonlinear damping behaviors for a lightweight motor-driven transtibial prosthesis," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 6, pp. 2512–2523, Dec. 2017.

[17] S. D. Prentice, E. N. Hasler, J. J. Groves, and J. S. Frank, "Locomotor adaptations for changes in the slope of the walking surface," *Gait Posture*, vol. 20, no. 3, pp. 255–265, Dec. 2004.

[18] A. S. McIntosh, K. T. Beatty, L. N. Dwan, and D. R. Vickers, "Gait dynamics on an inclined walkway," *J. Biomech.*, vol. 39, no. 13, pp. 2491–2502, Jan. 2006.

[19] N. Chia Bejarano, E. Ambrosini, A. Pedrocchi, G. Ferrigno, M. Monticone, and S. Ferrante, "A novel adaptive, real-time algorithm to detect gait events from wearable sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 3, pp. 413–422, May 2015.

[20] Y. Feng and Q. Wang, "Using one strain gauge bridge to detect gait events for a robotic prosthesis," *Robotica*, vol. 33, no. 5, pp. 245–263, 2019.

[21] C. C. Chang and C. J. Lin, "LIBSVM: A library for support vector machines," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 1–27, 2011.

[22] V. N. Vapnik and A. J. Chervonenkis, *Theory of Pattern Recognition*. Moscow, Russia: Nauka, 1974.

[23] H. Huang *et al.*, "Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 10, pp. 2867–2875, Oct. 2011.

[24] D. Xu, Y. Feng, J. Mai, and Q. Wang, "Real-time on-board recognition of continuous locomotion modes for amputees with robotic transtibial prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 10, pp. 2015–2025, Oct. 2018.

[25] E. Zheng and Q. Wang, "Noncontact capacitive sensing-based locomotion transition recognition for amputees with robotic transtibial prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 2, pp. 161–170, Feb. 2017.

[26] M. Liu, F. Zhang, and H. Huang, "An adaptive classification strategy for reliable locomotion mode recognition," *Sensors*, vol. 17, no. 9, p. 2020, Sep. 2017.

[27] E. Ceseracciu *et al.*, "SVM classification of locomotion modes using surface electromyography for applications in rehabilitation robotics," in *Proc. 19th Int. Symp. Robot Human Interact. Commun.*, Sep. 2010, pp. 165–170.

[28] J. A. Spanias, A. M. Simon, S. B. Finucane, E. J. Perreault, and L. J. Hargrove, "Online adaptive neural control of a robotic lower limb prosthesis," *J. Neural Eng.*, vol. 15, no. 1, Feb. 2018, Art. no. 016015.

[29] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

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