Oscillator-Based Hybrid Gait Phase Estimation Method for Hip Assistive Exoskeleton

MING-HANG TAN1, QIN-MU WU1, ZHI-QIN HE1, LIN LI2, BING QIU3, CHUN-SHAN LUO3, AND YI-MING XU1

1School of Electrical Engineering, Guizhou University (GZU), Guiyang 550000, China
2The 10th Research Institute of China Aerospace Science and Industry Corporation (CASC), Guiyang 550000, China
3Orthopaedic Hospital of Guizhou Province, Guiyang 550000, China

Corresponding author: Qin-Mu Wu (qmwu@gzu.edu.cn)

This work was supported by the Science and Technology Plan Support Project of Guizhou Province under Grant [2021]442.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Clinical Ethics Committee of Guizhou Orthopaedic Hospital.

ABSTRACT

To solve the problem of slow or lack of convergence of the gait phase estimation of the adaptive oscillator (AO) in the walking speed switching stage, this study designs an oscillator-based hybrid gait phase estimation method for hip assistive exoskeletons. First, the collected raw data of the hip angle are processed by performing Butterworth low-pass filtering. Then, by analyzing the characteristics of the hip angle curve and plantar pressure during each stage of walking, a divider that combines the hip angle, hip angular velocity, and plantar pressure is constructed to divide each gait cycle accurately. Finally, a phase estimator based on the angle model (AMPE) is proposed to replace the AO for phase estimation during the walking speed switching phase and to revert to AO for phase estimation when the walking speed is stable. By performing experiments of different walking speeds switching on the treadmill and outdoor walking scenarios, it is verified that the oscillator-based hybrid gait phase estimation method (AO+AMPE) has lower phase estimation errors and improves the gait feature estimation performance in the case of different walking speed switching, when compared with the AO-based phase estimation method and the hybrid phase oscillator-based (PO+AO) phase estimation method.

INDEX TERMS

Adaptive oscillator, gait cycle division, hybrid gait phase estimation, hip assistive exoskeleton, walking speed switching.

I. INTRODUCTION

In recent years, the degree of aging worldwide is increasing, and more and more people are suffering from lower limb dyskinesia caused by stroke, rheumatoid arthritis, and traffic accidents. With the development of science and technology, the emergence of lower limb exoskeleton has helped patients with rehabilitation training, overcomes the shortcomings of low efficiency and slow effect of traditional artificial rehabilitation training, and is beneficial for people with lower limb dyskinesia [1].

The lower limb exoskeleton mainly assists the lower limb movement through the output torque of the joint motor, so the method employed to design the assist control strategy of the lower limb exoskeleton is directly related to the effect of rehabilitation training [2]. Many scholars and researchers have proposed different assist control strategies.

1) Position tracking strategy based on predefined trajectory. Chen et al. [3] established a reference trajectory database of exoskeleton hip and knee joints in different motion processes, and used a proportional-differential (PD) controller to track the gait trajectory. Considering that there is coupling between the exoskeleton and human body when the human wears an exoskeleton for rehabilitation training, it is difficult to establish an accurate dynamic model. Zhu et al. [4] used a radial basis function neural network (RBFNN) to compensate the nonlinear relationship between human-robot systems, and proposed a gait trajectory tracking strategy based on...
an improved integral sliding mode controller. Chen et al. [5] designed an active disturbance rejection control (ADRC) using a fast terminal sliding mode controller (FTSMC) strategy, which can estimate the uncertain part and external disturbance part in human-robot systems through the extended state observer (ESO), and realized the stable tracking and rapid response of gait trajectory. However, these position tracking methods rely on artificial preset gait trajectories, which have poor matching for people with different degrees of lower limb paralysis. 2) Impedance control strategy. In order to improve the active interaction between humans and exoskeletons, Tran et al. [6] constructed an impedance control strategy based on the motion variation to solve the exoskeleton joint torque, and the impedance parameters were adjusted by the fuzzy logic rule using the respective angular velocities of human lower limbs and exoskeletons. Huo et al. [7] proposed a lower limb exoskeleton impedance parameter compensation method that calculates the impedance compensation term according to different standing vertical linear velocities in order to assist the elderly perform actions ranging from sitting to standing. The impedance model can reflect the dynamic relationship between the position and joint torque of the exoskeleton, but it needs to establish an accurate impedance model that inevitably leads to a large number of calculations of impedance parameters, so the online real-time tuning of impedance parameters is complex and costly. 3) Control strategy based on motion intention recognition. Lee et al. [8] used sensors to collect the surface electromyography (sEMG) signals of the human body to realize the perception of the wearer’s motion intention. Wang et al. [9] proposed a method to control the lower limb exoskeleton for assistance based on the brain-computer interface (BCI), which follows the wearer’s movement intention by decoding electroencephalography (EEG) signals and multimodal cognition. Although sEMG and EEG can be used to estimate human motion intention, the stability of sEMG and EEG signals is poor, and the signal acquisition sensors need to be used close to the human skin, which is inconvenient for humans. 4) Control strategy based on interaction force. Zanotto et al. [10] designed a force feedback controller that uses the interaction torque between the exoskeleton and the wearer’s leg as a feedback signal to reduce the inertial load transmitted by the exoskeleton link to the wearer. However, the collection of the interaction force requires the installation of interaction force sensors, which increases the complexity of the system. 5) Control strategy based on gait feature estimation. The gait feature of the human walking process can be described by two indicators, namely the gait cycle and the gait phase. If the assist control is carried out according to the gait feature of each stage of the human walking process, the assistance is more suitable for the gait habits of the wearers, the human-robot coordination will be higher. Ronsse et al. [11] verified the effectiveness of tracking the periodic signals using AO, and they indicated that AO can be applied to the lower limb exoskeleton assist control to estimate the human gait feature. Yan et al. [12] designed an AO gait feature estimation method based on an inertial measurement unit (IMU) to dynamically learn the gait signal, and their research results have great advantages with respect to both wearing adaptability and torque accuracy. In order to avoid the problem of abrupt change of angle data caused by the mounting of the IMU on the rigid node of the exoskeleton, Zheng et al. [13] used the capacitance data collected by the non-contact capacitive sensor system as the input of the AO, and his experiment also obtained a good estimation of gait phase.

Compared with other assist control methods, the gait feature estimation based on AO has obvious advantages, but the experiments reported in [12] and [13] were conducted under the condition of constant speed or small speed change, and the tracking effect of AO is poor during the speed switching stage [13]. To reduce the error of AO on gait phase estimation and improve the assist effect of lower limb exoskeletons during the speed switching, a hybrid gait phase estimation method based on oscillator was designed and presented in this paper. This method can ensure the accuracy of phase estimation between the stable stage and the switching stage of walking speed under the condition involving the use of only angle sensors and pressure sensors.

II. HYBRID GAIT PHASE ESTIMATION FOR LOWER LIMB HIP EXOSKELETON

The proposed oscillator-based hybrid gait estimation method proposed consists of six parts, namely a Butterworth low-pass filter, gait cycle divider, phase estimation selector, AO, AMPE, and phase reconstruction, as shown in Fig. 1.

A. BUTTERWORTH LOW-PASS FILTER

The Butterworth low-pass filter has a good suppression effect on high-frequency noise signals. If the filter order is properly selected, the phase delay of the filtered data will not be large [14]. Therefore, this filter is used to preprocess the raw hip angle and the raw plantar pressure. The frequency response of the filter is described as follows:

\[ |H(j\omega)|^2 = \frac{G^2}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}} \]

where \( \omega \) is the input signal frequency, \( \omega_c \) is the cutoff frequency, \( G \) is the gain, and \( n \) is the filter order. In this study, we choose \( n = 2 \) and \( \omega_c = 20Hz \).

B. GAIT CYCLE DIVIDER

The walking process of humans is a kind of periodic movement, and the action of each leg is always shown as stepping forward and retracting, which is repeated. The purpose of distinguishing gait cycle can be achieved by using sensors to detect the repeated characteristic event information during the walking process [15]. For example, using the IMU detects the angle or acceleration [16], and the force sensing resistor (FSR) detects the plantar pressure [17], [18]. However, people with lower limb dyskinesia encounter random shaking during
the leg swing process, which may lead to multiple local peaks and troughs in the hip angle curve collected by the IMU. The accuracy of dividing each gait cycle by the IMU alone will be affected. Considering that the foot activities during human walking are heel strike, toe support, toe off, and foot suspend completely [19], the pressure on the heel and toe will change regularly during the walking process. Therefore, this study designed a gait phase divider that combines the characteristics of the hip angle curve and the plantar pressure to perform real-time online partitioning of each gait cycle.

In this study, IMUs with a sampling frequency of 1000 Hz are selected to obtain the hip angle. The original hip angle is defined as $q$, and the hip angle after Butterworth low-pass filtering is defined as $q_{\text{filter}}$. $q_{\text{filter}}$ is normalized as

$$q_w = \frac{q_{\text{filter}} - q_{\text{filter, min}}}{q_{\text{filter, max}} - q_{\text{filter, min}}}$$  \hspace{1cm} (2)

where $q_w$ is the hip angle after normalization, $q_{\text{filter, min}}$ and $q_{\text{filter, max}}$ are respectively the minimum and maximum value of the hip angle after the filtering process.

Weighting sensors are installed at the toe and heel to obtain the original plantar pressure data $p$, and the filtered pressure data $P_{\text{filter}}$ is normalized as follows:

$$P_i = \frac{P_{\text{filter, i}} - P_{\text{filter, min}}}{P_{\text{filter, max}} - P_{\text{filter, min}}}$$  \hspace{1cm} (3)

where $i = 1, 2$ respectively represents the toe and the heel, $P_i$ is the plantar pressure data after the filtering process, and $P_{\text{filter, min}}, P_{\text{filter, max}}$ are respectively the minimum and maximum value of the plantar pressure after the filtering process.

During the normalization of the filtered hip angle and plantar pressure, the maximum and minimum values of the current gait are determined by the maximum and minimum values recorded in the previous gait.

Subtract $P_1$ from $P_2$ to obtain the plantar pressure difference $P_e$, which is designed as follows.

$$P_e = P_1 - P_2$$  \hspace{1cm} (4)

Fig. 2(a) shows the characteristics of the hip angular velocity $\dot{q}$, $P_1$ and $P_2$ in each gait cycle. Fig. 2(b) shows the characteristics of $q_w$ and $P_e$ in each gait cycle. Because the heel touches the ground, $P_2$ gradually increases, then the toe support and $P_1$ increases, and $\dot{q}$ is negative at this stage. When $P_1$ drops to 0, it indicates that the toes have left the ground, $P_1$ and $P_2$ are both 0, the foot is completely suspended, and $\dot{q}$ is positive in this stage.

According to the above characteristic information, a gait cycle divider combining $\dot{q}$, $q_w$, and $P_e$ is constructed. If the symbol of $\dot{q}$ is determined, the gait phase is divided when both $q_w$ and $P_e$ are simultaneously within their respective intervals in the division rule of Table 1. From an experimental point of view, the selected thresholds in Table 1 can satisfy the gait division requirements. However, the threshold conditions for gait division need to be adjusted appropriately according to the specific scenarios. In this study, we only need to obtain the beginning moments of the swing and support stage for the subsequent phase estimation, thus, the gait phase is divided into four phases according to the specific rule in Table 1, where IW is the initial swing phase, FW is the full swing phase, IS is the initial supported phase, and FS is the fully supported phase.

C. AO FOR PHASE ESTIMATION

Any periodic signal can be decomposed into multiple harmonics using the Fourier transform (FT). Ronsse et al. [11], [20] used AO to dynamically track each harmonic, and described the periodic signal with four state variables: amplitude, phase, frequency, and offset. Based on the error between the input signal and the output signal, AO continuously adjusts and constructs a nonlinear combination of dynamic
TABLE 1. Gait division rule.

| Gait phase | IS | FS | IW | FW |
|------------|----|----|----|----|
| \( \dot{q} \) | -  | -  | +  | +  |
| \( q_w \) | [0.4,1] | (0.0,4) | [0,0,2] | (0.2,1) |
| \( P_e \) | [-1,0] | (-1,1) | (0,0,6) | 0 |

changes of state variables in order to approximate the input signal. When AO reaches a steady state, the three state variables of amplitude, frequency and offset will converge to their respective stable values, and the phase state variable will oscillate over time [21], [22], [23]. AO can be formulated as follows,

\[
\dot{\varphi}_i(t) = \omega(t) \ast i + \nu_{\varphi} \ast \frac{e(t)}{\sum_{i=1}^{n} \alpha_i(t)} \ast \cos \varphi_i(t) \tag{5}
\]

\[
\dot{\omega}(t) = \nu_{\omega} \ast \frac{e(t)}{\sum_{i=1}^{n} \alpha_i(t)} \ast \cos \varphi_1(t) \tag{6}
\]

\[
\dot{\alpha}_i(t) = \nu_{\alpha} \ast e(t) \ast \sin \varphi_i(t) \tag{7}
\]

\[
\dot{\alpha}_0(t) = \nu_{\alpha} \ast e(t) \tag{8}
\]

where \( \omega \) represents the fundamental frequency of the input signal \( \dot{q}_{\text{filter}}(t) \), \( \varphi_i \) and \( \alpha_i \) are the phase and amplitude of the \( i \)-th oscillator, respectively, \( \alpha_0 \) is the offset of \( \dot{q}_{\text{filter}}(t) \), \( e(t) = \dot{q}_{\text{filter}}(t) - \dot{\varphi}_i(t) \) is the error between the input signal \( \dot{q}_{\text{filter}}(t) \) and the output signal \( \dot{\varphi}_i(t) \), \( \nu_{\varphi} \), \( \nu_{\omega} \) and \( \nu_{\alpha} \) are the learning rates of the phase, frequency, and amplitude, respectively. The AO’s effect of tracking \( \dot{q}_{\text{filter}}(t) \) can be improved by adjusting an appropriate learning rate. \( n \) is the number of oscillators learning the harmonic order of \( \dot{q}_{\text{filter}}(t) \).

The output signal \( \dot{q}_{\text{filter}}(t) \) of AO is given by

\[
\dot{q}_{\text{filter}}(t) = \sum_{i=1}^{n} \alpha_i(t) \ast \sin(\varphi_i(t)) + \alpha_0(t) \tag{9}
\]

The estimated phase \( \varphi_1(t) \) of AO is given by

\[
\varphi_1(t) = \int \omega dt \tag{10}
\]

According to the result of gait cycle divider in section II B, the moment at which IW occurs in each gait cycle is recorded as \( t_k \), and the final phase \( \varphi_{\text{inc}}(t) \) of AO can be expressed as below

\[
\varphi_{\text{inc}}(t) = \text{Inc}\int \frac{t - t_k}{2\pi} \ast \varphi_1(t), 2\pi \tag{11}
\]

where function \( \text{Inc} \) includes two input parameters: the percentage of the gait phase, and the gait phase amplitude. It multiplies these two parameters and returns the value of the gait phase at the current moment.

D. AMPE DESIGNED FOR PHASE ESTIMATION

Although AO has an excellent tracking effect on the periodic gait signal, when the period of the gait changes, the tracking effect of AO decreases significantly, and there will be slow convergence or even non-convergence. It is not difficult to determine that during the whole gait cycle, regardless of whether the period of the gait changes periodically or not, the hip angle always shows a characteristic similar to a sine curve from IW to FS because the standard gait phase always increases linearly from 0 to \( 2\pi \) during each gait [12]. Therefore, the hip angle and gait phase can be approximately positively correlated in the swing phase, and approximately negatively correlated in the support phase. Based on the above analysis, the AMPE is constructed to estimate the phase \( \varphi_{\text{ampe}} \) when the gait cycle is changing, which is defined as follows.

\[
\varphi_{\text{ampe}} = \begin{cases} 
\frac{q_w - q_{\text{WL}}}{q_{\text{WH}} - q_{\text{WL}}} \ast \varphi_{\text{mid}}, & \text{if gait = IW or FW} \\
\varphi_{\text{mid}} + \frac{q_w - q_{\text{WH}}}{q_{\text{WH}} - q_{\text{WL}}} \ast (2\pi - \varphi_{\text{mid}}), & \text{if gait = IS or FS} 
\end{cases} \tag{12}
\]

where \( q_w \) is the hip angle after normalization, \( q_{\text{WH}} \) is the maximum extension angle of the hip in the current gait, \( q_{\text{WL}} \) is the minimum flexion angle, and \( \varphi_{\text{mid}} \) is the gait phase at the time point when the FW is converted to the IS.

![FIGURE 2. The characteristics of hip angle curve and plantar pressure. (a) shows the characteristics of the hip angular velocity and the plantar pressure. (b) shows the characteristics of the hip angle and the plantar pressure difference.](image-url)
where \( i = H, L \) respectively indicate that the hip extension angle reaches the maximum value and the flexion angle reaches the minimum value, \( q_{wH}(k) \) represents the maximum extension angle of the \( k^{th} \) gait cycle, \( q_{wL}(k) \) represents the minimum flexion angle of the \( k^{th} \) gait cycle, \( \varphi_{mid}(k) \) represents that the gait phase at the switching time point of the \( k^{th} \) gait cycle. \( \lambda \) and \( \rho \) are weight parameters of \( n \times 1 \).

In this paper, \( n = 3, \lambda = [0.75, 0.15, 0.1]^T \) and \( \rho = [0.82, 0.16, 0.02]^T \) are selected, that is, the gait characteristics of the previous three cycles are used to estimate the gait features of the next cycle. However, the weight parameters need to be adjusted according to actual experimental situations.

### E. PHASE ESTIMATION SELECTOR

Subsection D proposes AMPE to compensate for the insufficiency of gait phase estimation by AO during the speed switching stage. However, determining how to assess whether the current gait is in the speed switching stage is obviously a problem that cannot be ignored. By observing the tracking of the hip angle curve by AO, the error between the angle estimated by AO and the actual angle is extremely apparent when the walking speed switching amplitude is large, however, when the walking speed switching amplitude is small, the angular frequency change is small, the error between the gait period estimated by AO and the actual gait period is not very apparent. Accordingly, this paper proposes a phase transition discrimination mechanism based on the normalized error of angle estimation (\( \hat{\varphi}_q(t) \)) and the normalized error of gait period estimation (\( \hat{\varphi}_T(t) \)).

During the period from the time \( t_{k-1} \) to \( t_k \), when IS of the last gait cycle occurs to the time \( t_k \) when the IS of the current gait cycle occurs, a dynamic error calculation rule is designed as below:

\[
\xi = \left( \hat{\varphi}_T(t) + \left( \hat{\varphi}_q(t) * k_p + k_i * \int \hat{\varphi}_q(t) \right) \right) * T/2
\]

where \( \xi \) is a dynamic error from \( t_{k-1} \) to \( t_k \), the proportional term \( k_p \) is used to control the credibility of the angular error, the larger the \( k_p \), the more apparent the angular error, the smaller the \( k_p \), the more apparent the period error. The integral term \( k_i \) is used to eliminate noise in the angular measurement. If the angular measurement has been zero-bias calibrated, \( k_i \) is commonly a minimal value. \( T \) is the embedded system control cycle of the exoskeleton prototype.

When \( |\xi| \) is greater than 0.5, it indicates that the learning effect of AO on the hip angle input signal from \( t_{k-1} \) to \( t_k \) is poor. The gait is currently in the speed switching stage, so AMPE is selected to estimate the phase until \( |\xi| \) is less than or equal to 0.5, the gait is currently in the speed stabilization stage, then AO will be resumed for phase estimation.

### F. PHASE RECONSTRUCTION

According to Subsection C, D, and E, the gait phase estimated by the oscillator-based hybrid gait phase estimation method can be reconstructed by

\[
\varphi = \begin{cases} 
\varphi_{ampe}, & |\xi| > 0.5 \\
\varphi_{inc}, & |\xi| \leq 0.5 
\end{cases}
\]

### III. EXPERIMENT AND RESULT ANALYSIS

#### A. EXPERIMENTAL PLATFORM

The experimental verification of all algorithms in this paper is completed on a lower limb hip exoskeleton prototype system (as shown in Fig. 3). The control system of the exoskeleton prototype is based on the ARM Cortex-M7 architecture chip STM32F765IJK6, with a clock frequency of 216 MHz, and running an RT-Thread operating system. The BLDC motor with a rated output torque of 45N·m and a rated output speed of 27 rpm is selected as the hip joint motor. The rated power of the motor FOC driver is 480 W, and the incremental encoder with a resolution of \( \leq 1^\circ \) is used to obtain the mechanical angle of the rotor.

When the subject wears the exoskeleton prototype, the IMUs (Type: JY931, WitMotion, China) are attached to the surface of an elastic bandage instead of being placed at the

![FIGURE 3. The lower limb hip exoskeleton prototype.](image-url)
rigid node outside the exoskeleton thigh link, and the elastic bandage will be tied to the middle of the legs, as shown in Fig. 4. This IMU has an integrated attitude fusion algorithm inside that can directly output tri-axial Euler angles. Based on the IMU installation shown in Fig. 4, we choose the pitch angle output from the IMU as the hip angle. Because the bandage is elastic, the discontinuity of the collected angle data can be prevented as much as possible when the lower limbs are extended or flexed. The flat pressure sensors (Type: DYHW-116, DAYSENSOR, China) with a range of 0–30 kg are embedded in the toe and heel of each shoe to obtain plantar pressure data. To avoid the situation that FSR may have signal errors or even failures, owing to electromagnetic interference and other factors, an open, cable-free area will be select as the experimental site, and apply the CAN bus protocol for signal transmission, and automatically ignore the signal data of the frame when the signal transmission is wrong or fail, which enhances the stability of data transmission.

Considering the safety of the wearers, the prototype is equipped with an emergency switch, which can be pressed to turn on or stop the machine. After the exoskeleton is powered on, all sensor data and gait characteristic data will be recorded in the memory card (Type: SDC4/4GB, Kingston, USA) for subsequent experimental data analysis.

The delay brought by the program iteration is approximately 1.2-1.5 ms as measured by the software method. Therefore, the control bandwidth of the exoskeleton system is set at 500Hz to satisfy the condition that the delay time within the control time, thus minimizing the impact of the delay problem.

### B. EXPERIMENTAL SETUP AND RESULT ANALYSIS

In order to verify the effect of the proposed oscillator-based hybrid gait phase estimation method for the walking speed switching stage, this study designed the treadmill experiment, the outdoor walking experiment, and the walk alternating experiment. The exoskeleton is operated in the active assist mode with torque output in the experiments. When the subject wears the exoskeleton, the maximum extension angle and minimum flexion angle will change to some extent (increase or decrease), but the four gait phases (IW, FW, IS, FS) of the wearer still exist, so the gait phase estimation is not affected.

#### 1) TREADMILL EXPERIMENT

The subject (height 175 cm, weight 62 kg) wore exoskeleton prototype and walked on the treadmill according to the sequence: still (0 km/h) → medium speed (2.2 km/h) → slow speed (1.8 km/h) → fast speed (2.4 km/h) → slow speed (1.8 km/h) → medium speed (2.2 km/h), as shown in Fig. 5. In addition to being still (0 km/h) for 10 s, the duration of other speeds is 60 s. It should be noted that the speed switching time of the treadmill is ignored in this study. Table 2 shows 10 sample data sets collected by the actual sensor.

#### TABLE 2. Sample data sets of the treadmill experiment.

| Speed (0 km/h) | Speed (1.8 km/h) | Speed (2.2 km/h) | Speed (2.4 km/h) | Total number of gait cycles |
|---------------|------------------|------------------|------------------|-----------------------------|
| 2044          | 12538            | 12009            | 5604             | 155                         |
| 1968          | 12040            | 12357            | 6011             | 165                         |
| 2138          | 11226            | 12341            | 6520             | 160                         |
| 2144          | 11517            | 12331            | 6236             | 136                         |
| 2310          | 11933            | 12598            | 6114             | 151                         |
| 2010          | 12184            | 12447            | 5764             | 148                         |
| 2190          | 12416            | 11831            | 5923             | 142                         |
| 2110          | 11933            | 12342            | 6010             | 136                         |
| 1890          | 12288            | 12372            | 6635             | 142                         |
| 1910          | 11646            | 12212            | 6165             | 138                         |

The phase estimation error (PEE) is defined by

$$PEE = \hat{\phi}_m - \varphi_m$$  \hspace{1cm} (19)
The average phase estimation error (APEE) in each gait cycle is expressed as follows:

$$APEE = \frac{1}{U_n} \sum_{m=1}^{U_n} |\hat{\phi}_m - \phi_m|$$  (20)

where $\hat{\phi}_m$ and $\phi_m$ are respectively the estimated phase and the actual phase of the $m^{th}$ sampling point.

### TABLE 3. Average phase estimation error.

|        | AO     | AO+PO  | AO+AMPE |
|--------|--------|--------|----------|
| 0->2.2 km/h | 1.931 rad | 0.889 rad | 0.719 rad |
| 2.2 km/h ->1.8 km/h | 1.547 rad | 0.887 rad | 0.516 rad |
| 1.8 km/h ->2.4 km/h | 1.497 rad | 0.901 rad | 0.392 rad |
| 2.4 km/h ->1.8 km/h | 1.498 rad | 0.904 rad | 0.380 rad |
| 1.8 km/h ->2.2 km/h | 1.256 rad | 0.886 rad | 0.407 rad |
| average   | 1.546 rad | 0.893 rad | 0.483 rad |

### TABLE 4. Root mean square of the phase estimation error.

|        | AO     | AO+PO  | AO+AMPE |
|--------|--------|--------|----------|
| 0->2.2 km/h | 0.851 rad | 1.254 rad | 0.735 rad |
| 2.2 km/h ->1.8 km/h | 0.823 rad | 0.991 rad | 0.411 rad |
| 1.8 km/h ->2.4 km/h | 0.730 rad | 1.015 rad | 0.309 rad |
| 2.4 km/h ->1.8 km/h | 0.729 rad | 0.818 rad | 0.344 rad |
| 1.8 km/h ->2.2 km/h | 0.578 rad | 0.712 rad | 0.265 rad |
| average   | 0.742 rad | 1.070 rad | 0.413 rad |
The root mean square of the phase estimation error (RMS) is calculated as follows:

$$RMS = \frac{1}{V} \sum_{n=1}^{V} \sqrt{\frac{\sum_{m=1}^{U_n} (\hat{\phi}_m - \phi_m)^2}{U_n}}$$  \hspace{1cm} (21)$$

where $V$ is the total number of gait cycles for each group of sample data.

The treadmill experiment contains five speed switching scenarios, which are $0 \rightarrow 2.2 \text{ km/h}$, $2.2 \text{ km/h} \rightarrow 1.8 \text{ km/h}$, $1.8 \text{ km/h} \rightarrow 2.4 \text{ km/h}$, $2.4 \text{ km/h} \rightarrow 1.8 \text{ km/h}$, and $1.8 \text{ km/h} \rightarrow 2.2 \text{ km/h}$. In this paper, the proposed hybrid gait phase estimation method based on oscillator (AO+AMPE) is compared with the IMU-based gait phase estimation methods.
(e.g., AO [12] and hybrid phase estimator PO+AO [24-25]) to verify the performance of gait phase estimation for the continuous speed switching stage, and the APEE and RMS results are shown in Table 3 and Table 4, respectively. As in [25], the hip angle and angular velocity, after filtering, are the inputs of the PO+AO method to obtain the gait phase, whereas the learning parameters of AO are the same as those of the AO+AMPE method.

It can be seen from Table 3 and Fig. 6 that the APEE of the AO, AO+PO, and AO+AMPE methods are respectively 1.931 rad, 0.889 rad, and 0.719 rad at the initial stage of treadmill startup (0 → 2.2 km/h). Regardless of the method used, the APEE of this speed switching scenario is the highest compared with other scenarios. Because this speed switching scenario is the initial stage of AO, each state variable of AO is at the initial value, and it takes time to learn and adjust. Therefore, the estimated value of the phase is quite different from the actual value. However, in the five speed switching scenarios, the APEE of the AO+AMPE is the smallest among the above three phase estimation methods. Table 4 and Fig. 7 reflect the RMS of the phase estimation error in the five speed switching scenarios. It can be seen that the RMS of the AO+PO method is the largest in each speed switching scenario, followed by the AO method, and the AO+AMPE is the smallest. In terms of the average phase estimation error in the five speed switching scenarios, the average APEE and average RMS of the AO method are 1.546 rad and 0.742 rad, respectively, for the AO+PO method they are 0.893 rad and 1.070 rad, respectively, and for the AO+AMPE method they are 0.483 rad and 0.413 rad, respectively. The average APEE and the average RMS of the AO+AMPE method are both a minimum.

Fig. 8 shows the case of hip angle tracking of the AO during walking speed switching. It can be seen that when the learning state of AO is set to 0, the learning effect of AO on the hip angle is poor, and the current gait is in the speed switching phase, when the learning state of AO is set to 1, the learning effect of AO on the hip angle is precise, and the current gait is in the speed stabilization phase. Fig. 9 shows the phase estimation linearity of the three phase estimation methods (AO, AO+PO, AO+AMPE) during the same speed switching period in the treadmill experiment. It can be seen from Fig. 9 that the phase estimated by the AO method will suddenly increase at the beginning of the speed switching period (72–74 s), and the phase estimated by the AO method will gradually become stable with continuous learning and adjustment. However, the linearity of the phase estimated by the AO+PO method is poor compared to standard phase, and the effect of using the phase estimated by the AO+PO method for torque assistance may not be ideal. Compared with the AO method, the phase linearity of the AO+AMPE method is reduced, but instead of an abrupt increase or decrease, the phase of the AO+AMPE method is closer to the standard phase, so the AO+AMPE method has the best linearity of phase estimation.

2) OUTDOOR WALKING EXPERIMENT

To differentiate from the first experiment and prevent the stiffness caused by the treadmill switching speed, we let another subject (height 178 cm, weight 55 kg) wearing the exoskeleton prototype walk freely in an outdoor playground for about 2 minutes, as shown in Fig. 10. The walking speed of the subject can be changed at any time during the whole outdoor walking experiment.

As can be seen from Fig. 11, when the walking speed changes, the gait cycle also changes, the larger the difference between the actual gait cycle (blue line in Fig.11 (b)) and the gait cycle estimated by the AO (red line in Fig.11 (b)), the worse the learning state of the AO for the hip angle signal (red line in Fig.11 (d)) will become 0, the phase estimated by the AO increases abruptly owing to the speed switch (blue line in Fig.11 (c)), and the AMPE will be used for the phase estimation at the current gait stage until the AO tracks the hip angle stably again (the blue line almost coincides with the
red line in Fig. 11(a)), the learning state of the AO (red line in Fig. 11(d)) will change to 1, and the AO will switch back for phase estimation.

The AO+AMPE method has the advantage of having a smaller error in the phase estimation during the speed switching stage, and the wearer does not feel the obstruction of the exoskeleton on the leg or the need for the leg to pull the exoskeleton with extra force during the whole free walking assistance experiment. Therefore, the AO+AMPE method proposed in this paper can ensure the accuracy of phase estimation and the flexibility of assistance between the stable stage and the switching stage of the walking speed, and it has a better human-machine coordination effect.

3) "STOP TO GO", "GO TO STOP" EXPERIMENT
Walking in daily life involves not only switching the walking speed but also scenarios from "stop" to "go" and from "go" to "stop". Therefore, to further verify the performance of the proposed AO+AMPE, a walk alternating experiment, containing both stop-to-walk and walk-to-stop scenarios, was designed. The subjects were asked to wear the exoskeleton to start walking after stopping, when stopping after a certain duration of walking, when continuing to walk after a period of time, and when stopping the walk. The motor of the exoskeleton joints had a torque of 0 because the stop phase did not require further assistance. Fig. 12 shows the angular tracking and phase estimation for the entire walk alternating experiment.

It can be seen from the shaded area of Fig. 12 (a) that the phase estimator changes from the AO to AMPE in the walk-to-stop scenario owing to the change in walking speed, after the stop-to-walk scenario, the phase estimator reverts from the AMPE to AO. Furthermore, with the change in human walking speed from walking to stopping and stopping to walking (Fig. 12 (b)), there is no abrupt change in gait phase shown in the shaded area of Fig. 12 (c), thus the AO+AMPE has the same good adaptation effect for gait phase estimation in the walk-to-stop alternating scenario.

4) GENERALIZED PERFORMANCE EVALUATION
To verify the adaptability and practical value of the proposed AO+AMPE method for phase estimation for different wearers, two additional subjects, one male (height 177 cm, weight 65 kg) and other male (height 166 cm, weight 52 kg), were added to the treadmill experiment and the outdoor experiment, respectively. In the treadmill experiment, each subject performed 10 sets of walking tests according to the treadmill speed switching requirement in the part 1 of Section III-B. Table 5 and 6 shows the APEE and RMS data of the treadmill experiment for different subjects, respectively. In the outdoor experiment, each subject was free to switch walking speed, and the number of speed switching was consistent with the outdoor experiment given in the part 2 of Section III-B. Fig. 13 shows the phase estimation plots of the outdoor experiment for different subjects. It can be seen from Table 5 and 6 that the APEE and RMS results of the two additional subjects are close to the APEE and RMS data results of Tables 3 and 4, respectively, it can be seen from Fig. 13(a) and 13(b) that the phase estimation of the two additional subjects is similar to Fig. 11(d). These
results indicate that the AO+AMPE method has some adaptability and practical value for the phase estimation of different wearers.

**IV. CONCLUSION**

In this paper, an oscillator-based hybrid gait phase estimation method is proposed to compensate for the shortcoming of the AO in the walking speed switching stage. A gait cycle divider is constructed using the hip angle, hip angular velocity and plantar pressure information to classify each gait cycle. Then, when the tracking of the hip angle signal by the AO converges slowly, or even when it does not, the phase selector system will adjust to the AMPE to estimate the phase, and AO reverts to the phase estimation until the walking speed is stable. The treadmill experiment, the outdoor walking experiment, and the walk alternating experiment with multi-speed switching are designed to demonstrate the effectiveness and superiority of the oscillator-based hybrid gait phase estimation method compared with the AO method and the AO+PO method. The experimental results show that the proposed AO+AMPE method has a lower phase estimation error and excellent phase estimation performance between the stabilization and the switching stage of walking speed under the conditions of using only angle sensors and pressure sensors. However, there are some limitations in this study, such as an insufficient number of experimental data sets, not considering the case of hemiplegic patients, which will be reflected in future related works.

**REFERENCES**

[1] B. S. Rupal, S. Rafique, A. Singla, E. Singla, M. Isaksson, and G. S. Virk, “Lower-limb exoskeletons: Research trends and regulatory guidelines in medical and non-medical applications,” Int. J. Adv. Robotic Syst., vol. 14, no. 6, pp. 1–27, Dec. 2017.

[2] Y. Ma, X.-Y. Wu, J.-G. Yi, C. Wang, and C.-J. Chen, “A review on human-exoskeleton coordination towards lower limb robotic exoskeleton systems,” Int. J. Robot. Automat., vol. 34, no. 4, pp. 431–451, Aug. 2019.

[3] B. Chen, X. Zhao, H. Ma, L. Qin, and W.-H. Liao, “Design and characterization of a magneto-rheological series elastic actuator for a lower extremity exoskeleton,” Smart Mater. Struct., vol. 26, no. 10, Oct. 2017, Art. no. 105008.

[4] S. Zhu, X. Jin, B. Yao, Q. Chen, X. Pei, and Z. Pan, “Non-linear sliding mode control of the lower extremity exoskeleton based on human-robot cooperation,” Int. J. Adv. Robotic Syst., vol. 13, no. 5, pp. 1–10, 2016.

[5] C.-F. Chen, Z.-J. Du, L. He, J.-Q. Wang, D.-M. Wu, and W. Dong, “Active disturbance rejection control with fast terminal sliding mode control for a lower limb exoskeleton in swing phase,” IEEE Access, vol. 7, pp. 72343–72357, 2019.

[6] H. T. Tran, H. Cheng, H. Rui, X. Lin, M. K. Duong, and Q. Chen, “Evaluation of a fuzzy-based impedance control strategy on a powered lower exoskeleton,” Int. J. Soft. Robot., vol. 8, no. 1, pp. 103–123, Jan. 2016.

[7] W. Huo, H. Moon, M. A. Alouane, V. Bonnet, J. Huang, Y. Amirat, R. Vaidyanathan, and S. Mohammadi, “Impedance modulation control of a lower-limb exoskeleton to assist sit-to-stand movements,” IEEE Trans. Robot., vol. 38, no. 2, pp. 1230–1249, Sep. 2021.

[8] S. Lee and Y. Sankai, “Power assist control for walking aid with HAL-3 based on EMG and impedance adjustment around knee joint,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Oct. 2002, pp. 1499–1504.

[9] C. Wang, X. Wu, Z. Wang, and Y. Ma, “Implementation of a brain-computer interface on a lower-limb exoskeleton,” IEEE Access, vol. 6, pp. 38524–38534, 2018.

[10] D. Zanotto, T. Lenzi, P. Steggall, and S. K. Agrawal, “Improving transparency of powered exoskeletons using force/torque sensors on the supporting cuffs,” in Proc. IEEE 13th Int. Conf. Rehabil. Robot. (ICORR), Jun. 2013, pp. 1–6.

[11] R. Ronse, S. M. M. D. Rossi, N. Vitiello, T. Lenzi, M. C. Carrozza, and A. J. Jipspeert, “Real-time estimate of velocity and acceleration of quasi-periodic signals using adaptive oscillators,” IEEE Trans. Robot., vol. 29, no. 3, pp. 783–791, Jun. 2013.

[12] T. Yan, A. Parri, V. R. Garate, M. Cempini, R. Ronse, and N. Vitiello, “An oscillator-based smooth real-time estimate of gait phase for wearable robotics,” Auotn. Robots, vol. 41, no. 3, pp. 759–774, May 2016.

[13] E. Zheng, S. Manca, T. Yan, A. Parri, N. Vitiello, and Q. Wang, “Gait phase estimation based on noncontact capacitive sensing and adaptive oscillators,” IEEE Trans. Biomed. Eng., vol. 64, no. 10, pp. 2419–2430, Oct. 2017.

[14] S. Sprager and M. B. Juric, “Inertial sensor-based gait recognition: A review,” IEEE Sensors J., vol. 15, no. 9, pp. 22089–22127, Sep. 2015.

[15] S. R. Sutradhar, N. Sayadat, A. Rahmam, S. Munira, A. K. M. F. Haque, and S. N. Sakib, “IIR based digital filter design and performance analysis,” in Proc. 2nd Int. Conf. Telecommun. Netw. (TEL-NET), Aug. 2017, pp. 1–6.

[16] J. Jang, K. Kim, J. Lee, B. Lim, and Y. Shim, “Online gait task recognition algorithm for hip exoskeleton,” in Proc. IEEE Int. Conf. Intell. Robots Syst., Dec. 2015, pp. 5327–5332.

[17] D. J. Hyun, H. Lim, S. Park, and K. Jung, “Development of ankleless active lower-limb exoskeleton controlled using finite leg function state machine,” Int. J. Precis. Eng. Manuf., vol. 18, no. 6, pp. 803–811, Jun. 2017.

[18] H. Kim, Y. J. Shin, and J. Kim, “Design and locomotion control of a hydraulic lower extremity exoskeleton for mobility augmentation,” Mechatronics, vol. 46, pp. 32–45, Jun. 2017.

[19] Y. Qi, C.-B. Soh, E. Gunawan, K.-S. Low, and R. Thomas, “Assessment of foot trajectory for human gait phase detection using wireless ultrasonic sensor network,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 24, no. 1, pp. 88–97, Jan. 2016.

[20] R. Ronse, T. Lenzi, N. Vitiello, B. Koopman, E. Asseldonk, R. K. Ramachandran, S. Redkar, and C. Wheeler, “Limit cycles to enhance human performance based on phase oscillators,” Neurorobots, vol. 11, p. 15, Mar. 2017.

[21] Y. Kawamura, T. Takeda, K. Kanda, K. Yokoi, T. Osada, and S. N. Sakib, “IIR based digital filter design and performance analysis,” IEEE Trans. Biomed. Eng., vol. 61, no. 9, pp. 2234–2243, Sep. 2014.

[22] T. G. Sugar, A. Bates, M. Holgate, J. Kerestes, M. Mignolet, P. New, and S. M. M. D. Rossi, “Technical constraints on leg exoskeletons during continuous multi-locomotion tasks,” Frontiers Neuro Robotics, vol. 11, p. 15, Mar. 2017.

[23] T. S. Kang, C. Y. Lee, J. Y. Koo, Y. S. Jang, H. Kim, J. K. Koo, and I. K. Shin, “Human motion tracking and control of powered lower-limb exoskeleton using humanoid mirror,” J. Robot. Syst., vol. 38, no. 2, pp. 1230–1249, Sep. 2021.

**TABLE 5. Average APEE for the two additional subjects.**

| Subjects | AO     | AO+PO | AO+AMPE |
|----------|--------|-------|---------|
| No.1     | 1.554 rad | 0.854 rad | 0.583 rad |
| No.2     | 1.388 rad | 0.988 rad | 0.447 rad |
| average  | 1.471 rad | 0.921 rad | 0.515 rad |

**TABLE 6. Average RMS for the two additional subjects.**

| Subjects | AO     | AO+PO | AO+AMPE |
|----------|--------|-------|---------|
| No.1     | 0.831 rad | 1.361 rad | 0.469 rad |
| No.2     | 0.597 rad | 0.995 rad | 0.523 rad |
| average  | 0.714 rad | 1.156 rad | 0.496 rad |
M.-H. Tan et al.: Oscillator-Based Hybrid Gait Phase Estimation Method for Hip Assistive Exoskeleton

[24] T. Yan, A. Parri, M. Fantozzi, M. Cortese, M. Musculo, M. Cempini, F. Giovacchini, G. Pasquinì, M. Munih, and N. Vitiello, “A novel adaptive oscillators-based control for a powered multi-joint lower-limb orthosis,” in Proc. IEEE Int. Conf. Rehabil. Robot. (ICORR), Aug. 2015, pp. 386–391.

[25] W. Yang, L. Xu, L. Yu, Y. Chen, Z. Yan, and C. Yang, “Hybrid oscillator-based no-delay hip exoskeleton control for free walking assistance,” Ind. Robot: Int. J. Robot. Res. Appl., vol. 48, no. 6, pp. 906–914, Nov. 2021.

MING-HANG TAN received the B.S. degree in electrical engineering and automation from the Southwest University of Science and Technology, Mianyang, China, in 2020. He is currently pursuing the M.S. degree in electronic information with the Guizhou University, Guiyang, China. His research interests include exoskeleton robots, quadcopter drone, and embedded Linux.

QIN-MU WU received the B.S. degree in automation and the M.S. degree in control science and engineering from the Guizhou University of Technology, in 2001, and the Ph.D. degree in control science and engineering from the Huazhong University of Science and Technology, Wuhan, China. From 2001 to 2003, he was worked with Huawei Technologies Company. He is currently a Professor and a M.S. Supervisor with the College of Electrical Engineering, Guizhou University. He has authored over 30 papers, more than ten articles included by SCI or EI. His current research interests include control theory and applications, networked control, electric vehicle transmission control, and deep learning.

CHUN-SHAN LUO received the Ph.D. degree from Chongqing Medical University, Chongqing, China. He is currently the Vice President of Guizhou Orthopaedic Hospital, and a Young Member of the Spinal Cord Injury Committee of the Chinese Society of Rehabilitation Medicine. He has long been engaged in clinical work, with good professional knowledge structure and experience in solving complex problems in this specialty, specializing in fracture and dislocation of the spine (cervical, thoracic and lumbar spine), spinal degeneration (cervical spondylosis, lumbar disc herniation, lumbar spondylolisthesis, lumbar spinal stenosis), the surgical and non-surgical treatment of spinal deformities (scoliosis, kyphosis), spinal tumors, and tuberculosis.

BING QIU is currently a Professor, a Master’s Supervisor, the President of Guizhou Orthopedic Hospital, the Vice President of Guizhou Medical Association, a member of Chinese Medical Association Sports Medicine Branch, the Director of Guizhou Sports Medicine Branch, and the Vice Director of SICOT China Digital Medical. He has won the titles of China Good Doctor, Guizhou May Day Labor Medal, Moral Model, and 2020 China Outstanding Dean. His research interests include joint and sports medicine.

LIN LI received the bachelor’s degree. He is currently an Engineer with the 10th Research Institute of China Aerospace Science and Industry Corporation (CASC), Guizhou, China. His research interests include exoskeleton system design, human–machine interaction, exoskeleton human–machine efficacy, and integrated drive.

ZHII-QIN HE received the B.S. degree in industrial electrical automation from the Guizhou Institute of Technology, Guiyang, China, in 1994, and the M.S. degree in control theory and control engineering from Guizhou University, Guiyang, in 2002. She is currently a Professor at Guizhou University. Her current research interests include modern power electronic technology and motion control.

YI-MING XU received the bachelor’s degree in automation major from Guizhou University, in 2021, where he is currently pursuing the master’s degree in control science and engineering. His research interests include control theory and its applications, exoskeleton.