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A New Adaptive Frequency Oscillator for Gait Assistance

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***Abstract*— To control exoskeletons for walking gait assistance, it is of primary importance to control them to act synchronously with the gaits of users. To effectively estimate the gait cycle (or the phase within a stride) of users, we propose a new adaptive frequency oscillator (AFO). While previous AFOs successfully estimated the walking frequency from joint angles as inputs, the new AFO, called particularly-shaped adaptive oscillator (PSAO) can estimate gait cycle from the same inputs, which would have required foot contact sensors in previous approaches. To predict the effects of PSAO-based gait assistance on human walking, it has been tested with neuromuscular walking simulation. In the simulation, the gait assistance system reduced the metabolic cost of walking for some assistance patterns. The walk ratio (step length per step rate) also changed as assistance patterns shifted in phase, which is meaningful because metabolic cost of walking in general is minimal at specific walk ratio. For a prototype exoskeleton we developed, the effect of gait assistance was experimented on a human subject walking on level ground and inclining slopes to verify the predictions from the simulation: (1) physiological cost index computed from heart rate significantly decreased indicating reduction in metabolic energy expenditure; (2) walk ratio was in fact controllable to an extent.**

I. INTRODUCTION

As people age, stride length decreases and step width increases, making them walk less efficiently [1]. The elderly tend to use more of hip muscles and less of ankle muscles than young people do [2], which is mainly due to weakened ankle push-off action. This redistribution of powers in leg joints downgrades energetics of walking because the ankle is the most energy efficient joint in the legs due to elastic energy recycling in elongated tendons. The low efficiency of walking could make it hard to walk a long distance, accelerating the degradation of walking ability.

To assist walking in the elderly with weakened leg muscles and even to slow down the degradation of walking performance, we have developed a gait assistance system that provides assistive power around hip joints. We expect that gait assistance will lower the physical load of walking exercise on the user below a certain level so that the exercise can be prolonged without getting tired too soon. Unless the user gains a habit of depending too much on the system, it may help the user increase the amount of exercise and maintain the ability to walk independently.

In our gait assistance system, a controller is required to synchronize the assistive power from the system to human walking. In this paper, we propose a new AFO, called particularly-shaped adaptive oscillator (PSAO), and a gait assistance controller based on it. PSAO estimates gait cycle — a biomechanical term referring to the phase of walking within a stride — directly from each hip joint angle based on a template pattern. Given an estimate of current gait cycle, the gait assistance controller determines assistance torque from a look-up table.

Gait assistance systems based on adaptive frequency oscillators (AFO) were previously reported in [3], [4], where AFO learned the walking frequency and foot switches detected the beginning of each stride to estimate the gait cycle. AFO was first introduced in [5] as a mechanism to learn frequencies of pseudo-periodic input signals. With PSAO, unlike the previous studies, foot switches are not required to estimate gait cycle, which is advantageous for practicality and portability.

Another gait assistance device for hip joints in [6] had a different approach. To adjust the phase difference between human motion and the oscillation of a virtual device, the frequency of the virtual device was adjusted and the actual device was then controlled to the frequency of the virtual device. Details on how the device was controlled or whether it would be possible to apply arbitrary assistive torque patterns as in our controller was unclear. They demonstrated that average walk ratio (WR) — ratio of step length to step rate — was increased in the elderly with the device.

In the paper, we first derive mathematical formulation of PSAO from a typical AFO. We then present two predictions from simulation studies that:

1) gait assistance will lower metabolic cost of walking;
2) adjusting assistive torque patterns will change the WR.

Both predictions are validated in pilot experiments.

II. GAIT ASSISTANCE CONTROLLER

For our gait assistance device, the gait assistance controller takes inputs from two hip joint angle sensors and estimates gait cycle to generate assistive torques around hip joints. The gait assistance controller consists of gait cycle estimation, slope/speed estimation, joint velocity/acceleration estimation and assistance torque generation as shown in Fig. 1.

A. Gait cycle estimation using PSAO

Phase is defined as a fraction of a cycle that has elapsed from its origin. For walking, gait cycle is the term for phase within a stride, duration from a heel-strike to the next by the same foot. Given an average hip joint angle trajectory of nominal subjects walking at normal speed as a reference, and a trajectory of hip joint angles as an input, the phase of PSAO converges to the gait cycle. This section formulates PSAO after briefly reviewing an AFO.

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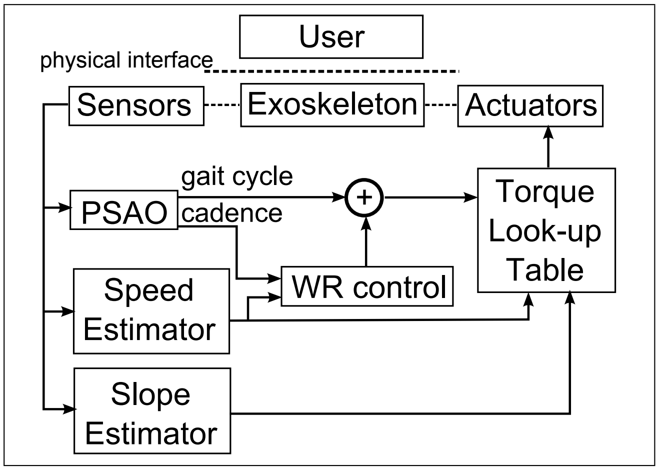

Fig. 1. Functional block diagram of the gait assistance system

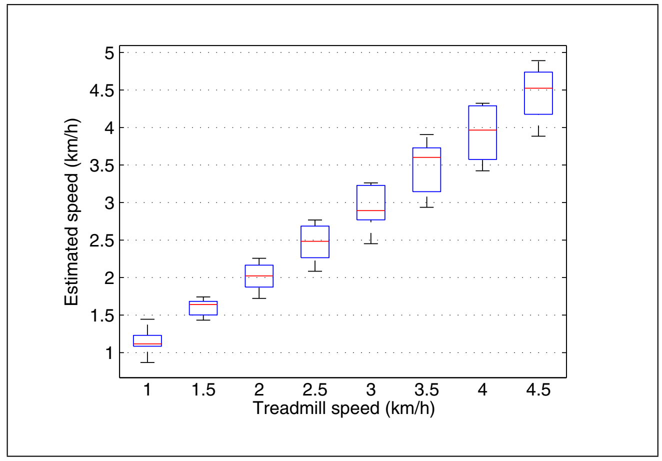

Fig. 2. Estimated speed vs. treadmill speed for 4 subjects

1) Typical AFO: If a signal u can be described as a linear combination of periodic signals oscillating at one frequency and its multiples, then AFO can *learn* the input using n oscillators, whose dynamics are described as, for $i = 1, \ldots, n$,

$$\begin{aligned}
\dot{\phi}_i &= i\omega + k_\phi e \cos(\phi_i) & (1)\\
\dot{\alpha}_i &= k_\alpha e \sin(\phi_i) & (2)\\
\dot{\omega} &= k_\omega e \cos(\phi_1) & (3)\\
\dot{\alpha}_0 &= k_o e & (4)\\
e &= u - \hat{u} & (5)\\
\hat{u} &= \alpha_0 + \sum \alpha_i \sin(\phi_i), & (6)
\end{aligned}$$

where α_i is the amplitude, ϕ_i is the phase of the i-th oscillator. α_0 is a non-oscillating component or a DC offset, and ω is the fundamental frequency of the input. $\hat{u}$ is the learned signal. Notice that ϕ_i is oscillating at frequency $i\omega$, the integer multiple of the fundamental frequency. Some rules to tune the gains k_ϕ, k_α, k_ω and k_o are found in [3].

2) PSAO: The idea of PSAO was encountered in seeking the physical meaning of ϕ_1 in AFO[1]. Suppose the input u is approximated by first three oscillators as

$$u = \alpha_0 + \alpha_1 \sin\phi_1 + \alpha_2 \sin\phi_2 + \alpha_3 \sin\phi_3 + \delta,$$

and $|\delta| \ll 1$. Then, we can replace the three terms with

$$f(\phi) = \alpha_1 \sin(\phi + \psi_1) + \alpha_2 \sin(2\phi + \psi_2) + \alpha_3 \sin(3\phi + \psi_3)$$

resulting in

$$u = f(\phi) + \delta.$$

PSAO can be formulated by replacing the basis function $\sin(\phi_1)$ of the first oscillator with $f(\phi_1)$, and $\cos(\phi_1)$ with $g(\phi_1) = \partial f(\phi_1)/\partial \phi_1$. PSAO algorithm works stably if 2π-periodic functions $f(\phi)$ and $g(\phi)$ are well defined for $\phi \in [0, 2\pi]$ and the mean of $f(\phi)$ is close to zero.

Since $f(\phi)$ is a mapping from phase ϕ to a periodic pattern, the PSAO can estimate the phase of the input as defined by $f(\phi)$. In our gait assistance controller, $f(\phi)$ is an averaged hip joint angle pattern in nominal human walking with ϕ being gait cycle and $\phi = 0$ indicating heel-strike. The phase ϕ_1 in PSAO then converges to the gait cycle when a joint angle trajectory is given as an input.

The PSAO is formulated as

$$\begin{aligned}
\dot{\phi}_1 &= \omega + k_\phi e g(\phi_1) & (7)\\
\dot{\alpha}_1 &= k_\alpha e f(\phi_1) & (8)\\
\dot{\phi}_i &= i\omega + k_\phi e \cos(\phi_i),\ (i = 2, \ldots, n) & (9)\\
\dot{\alpha}_i &= k_\alpha e \sin(\phi_i),\ (i = 2, \ldots, n) & (10)\\
\dot{\omega} &= k_\omega e g(\phi_1) & (11)\\
\dot{\alpha}_0 &= k_o e. & (12)
\end{aligned}$$

The estimated input $\hat{u}$ becomes

$$\hat{u} = \alpha_0 + \alpha_1 f(\phi_1) + \sum_{i=2,\ldots} \alpha_i \sin(\phi_i) \qquad (13)$$

A typical converging behavior of PSAO is shown later with simulation.

B. Speed and slope estimation

The speed and slope of walking are estimated using the joint angle trajectories, the cadence estimated by PSAO, and accelerations measured with a sensor on the back of the device. After collecting experimental data at different speeds and slopes, regression equations were obtained.

For example, walking speed is estimated by sensing acceleration on the back as

$$v = p_0 + p_1 < |a_x| >_{step} + p_2 < |a_z| >_{step} \qquad (14)$$

for some constants p_i, where $< |a_x| >_{step}$ and $< |a_z| >_{step}$ are mean absolute values of forward and vertical accelerations over a step, respectively. The boxplot in Fig. 2 illustrates speed estimation from 4 subjects walking on a treadmill.

Based on the estimated speed and slope, the controller interpolates predefined assistance torque patterns to ensure speed/slope adaptability.

[1]In a typical AFO, ϕ_1 should be the phase of input signal in comparison with $\sin(\phi_1)$ whose fundamental frequency is ω.

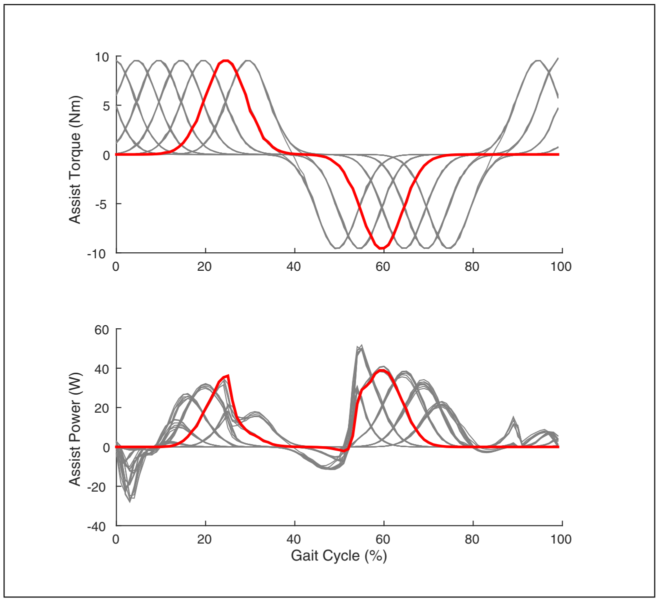

Fig. 3. 48 torque patterns are overlapped for extension peaks centered at 0, 5, 10, 15, 20, 25, 30 %GC and flexion peaks at 50, 55, 60, 65, 70, 75 %GC. Each torque patterns consists of an extension peak and a flexion peak. For clear presentation, one typical pattern is highlighted with red lines and others are drawn in gray.

C. Assistance torque generation

Given gait cycle, speed, and slope, assistance torque profile is determined from a multi-dimensional look-up table. Torque profiles in the table are designed by referring to studies on human gait [7], [8] at different speeds and slopes. It was then further tuned after testing on multiple subjects based on their verbal feedbacks.

D. Friction and inertial force compensation

To deliver the assisting torque correctly to human subjects, friction in the system needs to be compensated as well as the inertial forces due to the thigh frames and motors. The friction coefficients are obtained by system identification techniques; the moment of inertia of frames and motors by referring to design parameters. In addition to such parameters, joint velocity and acceleration signals are required for compensation. To avoid adding undesirable delays to the signals, we adopted a kernel-based nonlinear filter introduced in [3]. Since pseudo-periodic motions are predictable to some extent, the filter can estimate the joint velocities and accelerations without delays.

III. Predictions on the effect of gait assistance

To predict the effect of the gait assistance controller on human gait, we adopted a 2-dimensional bipedal walking simulation with neuromuscular system from the literature and extended it to include gait assistance system. In [9], Geyer *et al.* has shown that the combination of human musculoskeletal mechanism and reflex system could cause robust walking gait without any brain or rhythm generator.

The model had 1 link for trunk and 3 links for each leg. Leg muscles were modeled with 7 muscle groups — gluteal group (GLU), hip flexor group (HFL), hamstring (HAM), vasti group (VAS), gastrocnemius (GAS), soleus (SOL), and tibialis anterior (TA) — that governed motion in the lateral plane. Despite the limited dimensions and degrees of freedom, the resulting motion resembled human gait in joint angle/torque patterns as well as muscle stimulation patterns to some extent.

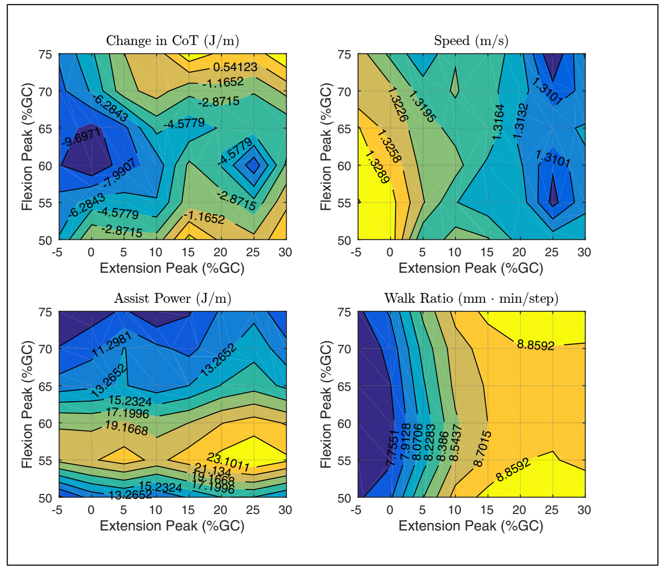

Fig. 4. The distributions of CoT (minus baseline CoT), walking speed, assisted power, and walk ratio (WR) are plotted. Two local minima were located in CoT distribution at (0, 60)%GC and (25, 60)%GC.

A. Predictions on cost of travel and walk ratio

We simulated the neuromuscular model for various assistive torque patterns with different extension and flexion phases to see if some torque patterns could reduce cost of travel (CoT), energy consumed per unit distance traveled. CoT was computed using Umberger *et al.*'s formulation (see [10]) for metabolic energy expenditure in muscles. The torque patterns that we simulated are shown in Fig.3. Each torque pattern consisted of one extension peak and one flexion peak. For simplicity, only the phases of the extension and flexion peaks were varied without changing their shapes and amplitudes. Extension and flexion torque peaks were Gaussian-like functions centered at -5, 0, 5, ..., 30 and 50, 55, 60, ... , 75 %GC[2], respectively.

The baseline CoT was computed from the simulation without assistance. The Fig. 4 shows the resulting distribution of CoTs from all the assistance patterns minus the baseline CoT. Negative values indicate that CoT were reduced due to assistance. Two local minima were located at (0, 60) and (25, 60) %GC. Additional simulations were performed with additional extension and flexion peaks around each local minimum with 2 %GC intervals. We then found the local minima at (-2, 62) and (25, 62) %GC as in Fig. 5. The CoT values were 260 and 268 J/m, respectively, corresponding to 19 and 11 J/m reductions from the baseline CoT of 279 J/m.

[2]Percent gait cycle (%GC) represents gait cycle in percents

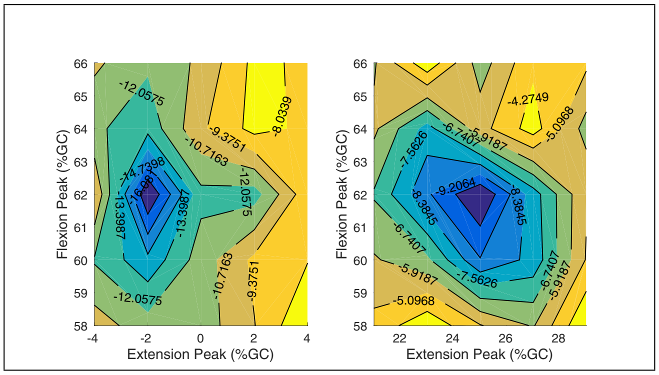

Fig. 5. The changes in CoT from the baseline were investigated around the two local minima found in 5-% grids. In 2-% grids, the minima were found at (-2, 62) and (25, 62) %GC.

We also observed that walk ratio changed as the assistance torque pattern changed as shown in Fig. 4. The baseline WR was 8.7 mm·min/step, and the WR decreased to 7.6 mm·min/step at (-2, 62) %GC and increased to 8.8 mm·min/step at (25, 62) %GC.

In Fig. 4, mechanically assisted CoT, or the assistance power divided by walking speed, is shown. The assisted CoT was 16 J/m at (-2, 62) %GC and 20 J/m at (25, 62) %GC. Interestingly, the reduction in CoT at (-2, 62) %GC was 19 J/m, which was larger than the supplied CoT by assistance system.

From the observations above, we predicted that for some individuals the CoT could decrease for some torque patterns; and that the walk ratio would decrease as the extension peaks shift to the left on the phase horizon and vice versa. We could not predict, however, whether the same torque patterns found from the simulation would be the optimum for human subjects. Besides the limitation that the model had less degrees of freedom than humans do, the simulated gait was not optimized for CoT and there was no mechanism to adapt on-line to minimize its CoT as humans may. In this regard, it was possible that the model was walking with inefficiently high walk ratio (8.7 mm·min/step) in the baseline simulation and the extension/flexion peaks at (-2, 62) %GC reduced the walk ratio to 7.6 mm·min/step bringing down near to optimum value of human. CoT in human walking is, in fact, minimal when WR is at a specific value. WR remains almost constant regardless of speed for an individual as was shown in [11], [12][3]. Considering the relationship between WR and CoT, it was unclear if the reduction in CoT from the simulation was due to change in the walk ratio or the power supplied from gait assistance. To isolate the factors, we need to optimize the model in terms of CoT in the presence of gait assistance, which is not included in the current research.

For the simulations above, we controlled the walking speed with a modification in the original model. The speed range in Fig. 4 indicates the speed range was quite narrow despite the large change in WR and CoT. When the simulations were repeated without speed controls, speed variation was much larger while the distribution of CoT was similar to the speed-controlled cases.

[3]It was mentioned in [12] that, for healthy subjects under their 60's, the WRs in mm·min/step were found around 6.4, and for older subjects around 5.5 to 4.4.

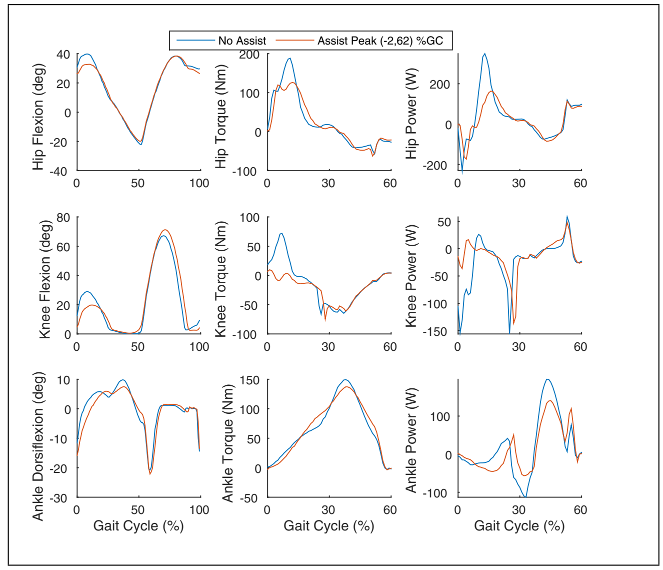

Fig. 6. Ensemble averages of left joint angles, torques and powers are plotted for the baseline (no assist) and assisted conditions. Torques and powers are plotted only before 60 %GC, where most differences were found.

B. Effects on joint kinematics and muscle usage

For the 2 simulation cases without assist and with extension/flexion peaks at (-2, 62) %GC, the joint angles, torques, and powers are compared in Fig. 6. Although the assistance was applied only at the hip joints, the changes were found in all the joints for both kinematics and kinetics.

The metabolic energy expenditure per unit distance traveled for each muscle is compared in terms of temporal pattern over gait cycle (Fig. 7) and net amount (Fig. 8).

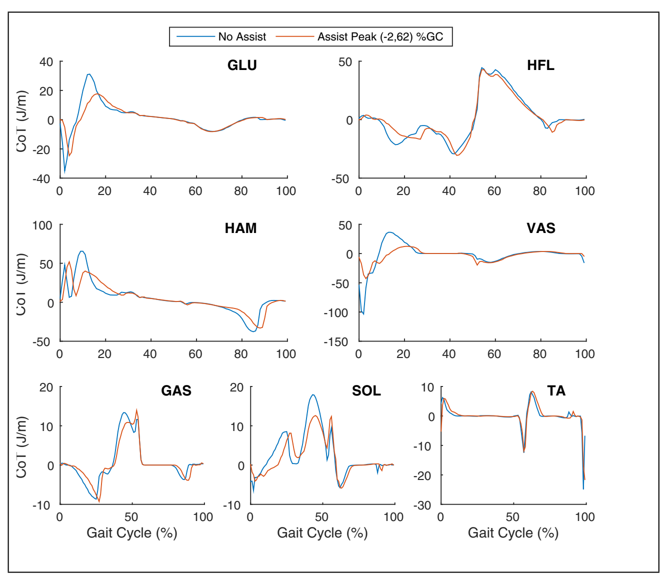

Fig. 7. Metabolic energy expenditure by muscle per unit distance traveled is affected by gait assistance.

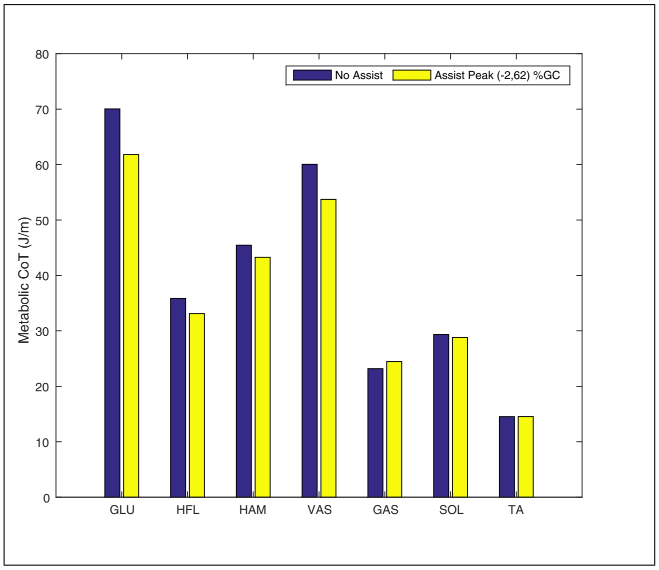

Fig. 8. Average CoT for each muscle is compared for assisted and non-assisted conditions. Significant decrease in GLU and VAS, which govern hip and knee extensions, are noticed.

Fig. 10. The prototype device was developed to be wearable around hip joints without any external tethers for control or power.

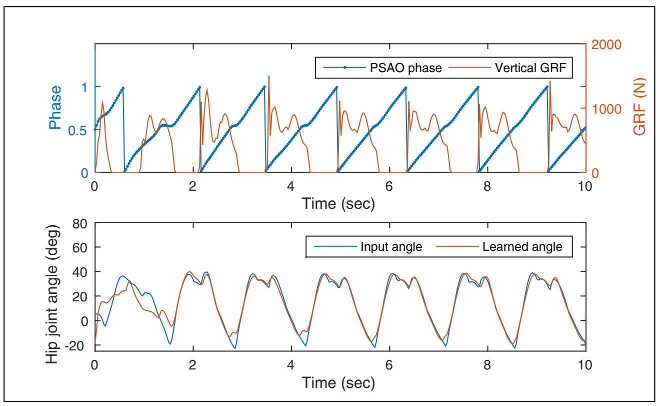

Fig. 9. PSAO phase and vertical ground reaction force synchronize as PSAO angle learns input joint angle.

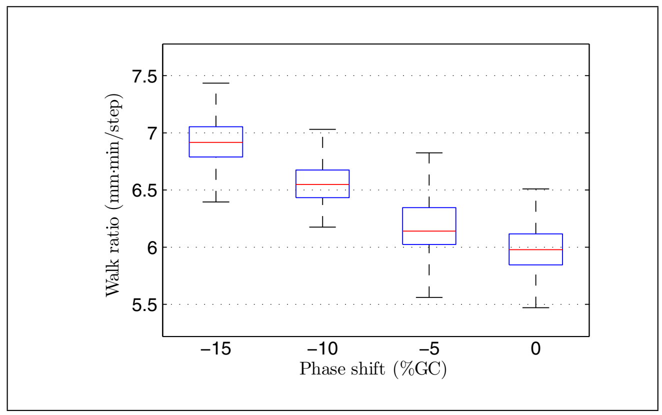

Fig. 11. The walk ratio was increased as the assistance torque pattern was delayed (or shifted to the right on the phase horizon) for 5, 10, and 15 %GC. The subject walked on a treadmill at constant speed of 4 km/h.

C. Convergence of estimated gait cycle

To visualize how the gait cycle estimation converges, PSAO phase during walking simulation is plotted with ground reaction force in Fig. 9. The output of PSAO, $\hat{u}$ in (13), is also plotted to show the learning process. Starting points of PSAO phase synchronized with the onsets of foot contact in a few strides after the model started walking.

IV. Experimental Results

To verify the prediction that gait assistance can reduce metabolic energy expenditure during walking, and also can adjust walk ratio, we performed the following experiments with an actual gait assistance device.

A. The Prototype Device

We developed a gait assistance device to assist the walking of the elderly with weakened muscles (Fig. 10). The device is fastened around the waist and around the thighs a few inches above knees to provide torques in the hip joints. The 2 joints are driven by electrical motors. The motors, battery, and a computer are mounted on the back of the device, which together weigh about 4 kg. It has joint angle sensors and an inertial measurement unit (IMU). The system can produce 10 Nm torque nominally.

B. Walk ratio control

As predicted in the simulation above, the phase shift in the assistance torque affects the walk ratio of a human. In fact, the relationship between phase shift in assistance torque and walk ratio was observed in our experiment. When the phase of assistance torque was shifted to certain values, the resulting walk ratio of our subject changed accordingly as illustrated in Fig. 11.[4]

Hence, we can infer that the gait assistance controller can control the walk ratio of the subject by shifting the phase of the assistance torque pattern. We applied a P-type feedback controller to make the subject's walk ratio approach

[4]Since the phase shift in the figure was added to the estimated gait cycle, negative phase shift actually delays the output of assistance torque.

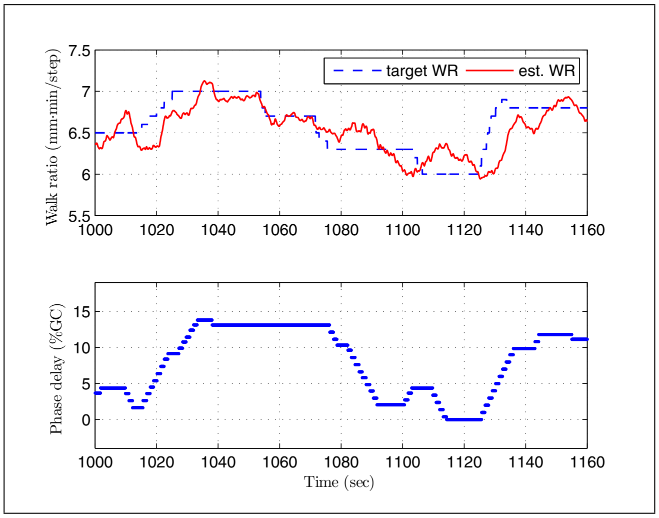

Fig. 12. The walk ratio of a subject is controlled to desired values by modulating phase delay in assistance torque.

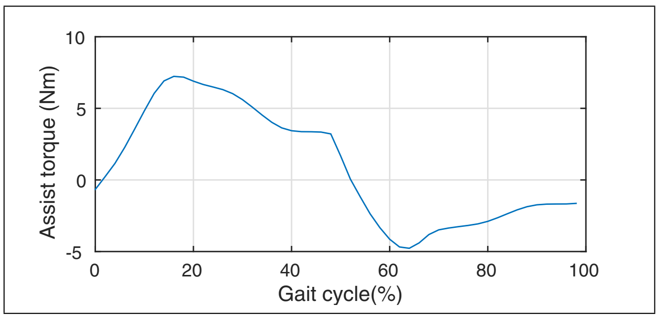

Fig. 13. Assistance torque pattern for experiments

the desired values. Fig. 12 shows how the controller actually changed the phases of the assistance torque to track the target walk ratio that changed over time.

C. Assistance torque and power

For the experiments, the assistance torque pattern in Fig. 13 was used, which was heuristically derived as explained above in Sec. II-C. Frictional and inertial force compensation torque was added to the assistance torque. The resulting assist power was computed by multiplying assistance torque and joint velocity, which is shown, after compensating for phase shift, in Fig. 14. Notice that the assist power was positive for most of the gait cycle.

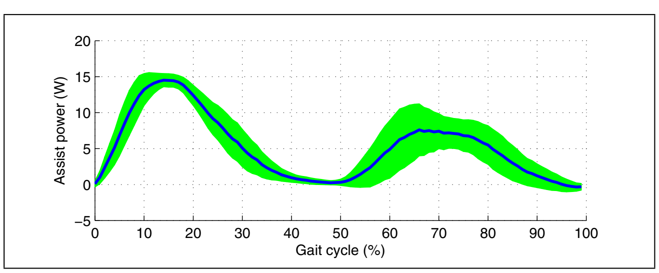

Fig. 14. Power pattern of the gait assistance system is plotted. Shade represents standard deviation.

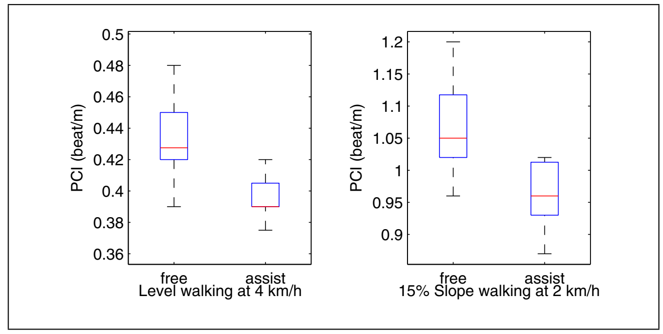

Fig. 15. PCI for level and slope walking shows decreased values when gait assistance system is used. Performing one-way analysis of variance on the HR data yields $p < 0.01$ for both level and slope walking, indicating that the PCIs are significantly lowered with gait assistance.

D. Metabolic energy expenditure

To show the effect of the gait assistance system quantitatively, we adopted physiological cost index (PCI), a practical and reliable measure of work load during walking exercises[13]. PCI is computed by measuring heart rate (HR) as

$$PCI = \frac{\text{Working HR - Resting HR (bpm)}}{\text{Walking speed (m/min)}} \tag{15}$$

We had a single test subject in his 40s with height 1.63 m and weight 63 kg. Experiments were performed on a treadmill for level and 15% slope. Each of the level and slope walking was done twice, once free without the device, and then with the assist. Level walking was at a fixed speed of 4 km/h and slope walking at 2 km/h. The subject wore a wireless HR sensor attached on the chest, and an experimenter read and manually recorded the HR values.

Since steady-state PCI is more reliable than non-steady-state PCI or post-exercise PCI according to [13], we use HR measurement from some time after the experiment has started. Slope walking experiments lasted for 400 seconds, HR was measured every 20 seconds, and the data from 200 to 400 seconds were used for statistical analysis; Level walking experiments lasted for 630 seconds, HR was measured every 10 seconds, and the data from 300 to 630 seconds were used. The resulting distributions of PCIs are illustrated in Fig. 15. The result indicates that for both level and slope gait assistance system reduces PCI significantly.

V. Discussion

The paper proposes PSAO, a new type of AFO, that estimates physically meaningful phase of a system such as gait cycle, and demonstrates its use for the application of a gait assistance system. The gait assistance controller generated assistance torque patterns by referring to predefined torque pattern with some modulations including speed/slope adaptation and walk ratio control. The walk ratio control was introduced to compensate the lack of optimality in the predefined torque pattern. Experiments proved that walk ratio in a human subject is actually controllable within a range of walk ratio while the simulation verified that walk ratio and CoT are closely related.

Regarding the CoT and WR, we presented an interesting case from the simulation when the reduction in CoT exceeded the CoT supplied by the assist system. Hence, we may hypothesize that the gait assistance system changing the WR in addition to supplying power also can reduce energy expenditure in walking although it requires more work to isolate the two factors: assistance power and WR.

The simulation had limitations: the model was in 2-dimensional plane with limited degrees of freedom, and that model did not include neural adaptation mechanism to minimize CoT in presence of assistance torques. The experiment for measuring PCI had limitations: it was a single subject; heart rate may reflect other factors than metabolic energy consumption. To address it, metabolic energy measurement experiments with more subjects and pulmonary measurement are planned.

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