An Event-Driven Control to Achieve Adaptive Walking Assist with Gait Primitives

Bokman Lim, Kyungrock Kim, Jusuk Lee, Junwon Jang, and Youngbo Shim

Abstract—This paper presents a control method for walking assist with hip-mounted exoskeleton robots. For modeling a user’s current walking motion, a novel finite state machine is first constructed. We divide a walking cycle uniformly using the inevitable zero crossing events. When state transitions occur, we capture the current walking spatio-temporal sensor data as discrete form. By using the sensed hip data as boundary conditions, we also develop a gait primitives based motion reconstruction method. Gait primitives are a form of basis trajectories to represent various joint motions. From those methods we estimate the moment of heel landing with interpolated knee joint motions. Utilizing the user’s previous opposite step motion, we predict the positive or negative work intervals of the current step motion. This makes it possible to achieve natural ‘one shot’ assist by driving adapted torques fast. This assist strategy is also effective to enhance gait regularity. The measures of stride time variability are improved by over 30% for the simulated experiment. Various real experimentations demonstrate the feasibility of our approach.

I. INTRODUCTION

Recently wearable devices for health-care have been received a lot of attention. As the proportion of the older people have increased, the related wearable technologies also have increased. Sensing and machine learning technologies already have been applied to commercial activity trackers. On the other hand, actuated wearable devices have been used in limited fields such as rehabilitation in hospitals [1], [2].

The main reasons for the limited use are safety and effectiveness in walking assist (older people are more vulnerable to device malfunction). The device should be lightweight and soft but sufficiently stiff to efficiently transfer assistive force. In the respect of control, the user’s intention and walking style should be sensed quickly. To guarantee walking safety and natural power assist without uncomfortableness, assist should be adaptable to the user’s walking style.

To synchronize the human-robot interactive motion, many researchers have used neural oscillators. Holgate et al [3] has proposed the control algorithm based on phase plane invariants. Miyake [4] has suggested the walk-mate walking support agent using the phenomenon of oscillation entrainment (two walking rhythms adapt mutually after the start of interaction). The role of the walk-mate is the guidance of the user’s walking rhythm. Honda’s stride management system [5] also uses this synchronization control technology. Lenzi et al. [6] have suggested an adaptive oscillators for the estimation of the gait phase and they have found that providing assistance only to the hip joint, both hip and ankle muscle activations could be reduced.

However, the oscillator based control methods have disadvantages in irregular (low periodicity) walking because a sudden pattern change needs time to converge in the coupled oscillators. Our target users are elderly people with gait abnormalities and the goal is to assist in joint power generation while helping with foot clearance. The main characteristics of the elderly people walking are slow and irregular walking with short step lengths (see [7]). But actuating an assistive device with a large torque is not a simple problem especially with limited sensors (one mismatched assist can significantly affect walking stability). In fact, most previous methods use relatively small mutual torques (e.g., 3~4 Nm [8], [9], or generate torques that are slowly increased for users to adapt [6]).

To better estimate the current user’s walking motion with only hip joint motions, we emulate the human capability of storing and reusing movement modules (i.e., the paradigm of movement primitives). Mataric and colleagues have, through the analysis of human motions, extracted movement primitives as joint trajectories using principal component analysis (PCA), and used them to generate and classify motions for robots [10]. Recently Liu and Liang have also developed human motion reconstruction using probabilistic principal component analysis [11].

In work prior to this paper, Lim et al, developed movement primitives based motion generation (i.e. knee swing [12] and arm reaching [13]). We extend that method to apply for walking assist robot. Note that we do not focus on reconstructing exact human knee joint profile. We instead focus on estimating the timing of the heel landing. Furthermore
we reflect the personal gait characteristics or abnormalities by using individual motion capture data. In this paper we restrict the case with only level and normal walking.

Our main contribution is the development of an event driven control method for natural walking assist with only hip joint motion. Most previous event driven (or discrete phase driven) based methods use simple on-off triggering control using individual state model for each joint or need additional sensors such as foot force sensor [14], [15] or bio-signal sensing unit [16].

We divide a walking cycle uniformly at the zero crossing events (e.g., crossing legs, changing swing direction). When state transitions occur, we capture the current walking spatio-temporal information (i.e., state time and joint angle) as discrete data. We sense the hip motion with the joint angle sensor but the rest knee motion is reconstructed online via linear interpolation of the principal component basis functions (gait primitives). The gait primitives are constructed offline; this is done by capturing walking motions for various speed, extracting dominant principal components, and forming basis functions.

Utilizing the users’ previously sensed and reconstructed knee motions, we are able to predict the positive or negative work intervals of the current step motion. This step-based (not stride) assist strategy makes it possible for a fast recognition of the current walking motion states. Finally, we achieve natural assist by generating appropriate assistive torques.

II. FRAMEWORK AND ALGORITHM

![Walking assist control framework](image)

Our control framework for walking assist is shown in Fig. 2. In this paper, we use a prototype developed by our research group which is driven with only two hip actuators (see Fig. 1). For a compact fit, the prototype uses a tendon-based remote actuation mechanism. To prevent uncomfortable force concentration on thigh, uniform-pressure fastener is also developed. The detailed hardware specifications will be presented with other publication. Using the device, we can only sense the hip joint motion while the knee joint motion is estimated by the gait motion reconstructor. The sensed and reconstructed motions are used to determine the current walking states and assist profile parameters in the gait state estimator. Using the gait parameters, we adaptively generate assistive torque profiles for the ensuing step motion.

A. Finite State Machine for Walking Motion Model

To estimate the current walking state, we design a finite state machine model as shown in Fig. 3. We first choose 4 major walking events E1,...,E4 as zero crossing conditions, i.e., zero hip velocity before retracting swing leg and zero hip angle difference when crossing both legs. We select two sub events E5 and E6 to detect heel landing events. The E5 and E6 are determined by crossing knee angle condition in states S1 and S3 (obviously we cannot directly sense knee angle motion). The state transition condition for heel landing event is determined from observing knee motion data (see Fig. 4). This state machine model works well in various walking styles (e.g., in slow speeds below 1km/h) and as well as in various environments (e.g., ramp, stairs). The detected heel landing timing is sufficiently accurate to be used as the start timing of the swing leg (flexion) assist (see Section IV).

![Suit-typed sensor testbed and its recorded data](image)

Fig. 4. Suit-typed sensor testbed and its recorded data. For various sensor data acquisition and algorithm validation, a sensor testbed is developed. Sensor testbed has joint angle sensors at hip/knee/ankle, foot force sensors at sole, inertial measure sensors at waist/thigh/foot.

B. Gait Primitives based Motion Reconstruction

![Example knee principal components for S1-S2](image)

Fig. 5. Example knee principal components for S1-S2 (left: captured knee joint angle trajectories and its mean value, right: first three principal components).

We first collect a walking motion data (joint motion data in sagittal plane) using a sensor testbed as shown in Fig. 4. A subject performs treadmill walking with various speeds (2~3.5km/h) for five minutes. We select 100 sample joint trajectories for 100 walking cycles (spline curve fitted with 50 uniform via points within a normalized time). We then segment the motions according to the walking states S1-S2 and S3-S4. Finally we perform a principal component analysis for each state interval (S1-S2, S3-S4); see [12], [13] for the detailed PCA procedure. The results of Fig. 5 suggest that the first three principal components alone are sufficient
to represent over 95% of the original motion data; for this reason, we use only the first three principal components. The principal components are the form of joint trajectories. So the knee motion primitives are composed of the 3 principal joint trajectories and the sample mean trajectory. Each trajectory is stored with 11 uniform via points and interpolated with Catmull-Rom spline method. For example, knee motion primitives for S1-S2 are a form of 4 joint trajectories (3 Catmull-Rom spline method. For example, knee motion primitives are composed of the 3 principal joint trajectories and the sample mean trajectory. Each trajectory is stored with 11 uniform via points and interpolated with Catmull-Rom spline curve for the current step.

\[ q_{knee}(t) = x_1 \cdot PC1(t) + x_2 \cdot PC2(t) + x_3 \cdot PC3(t) + \bar{q} \]  

(1)

where \( \bar{q} \) is a sample mean trajectory. The coefficient values \( x_1, x_2, x_3 \) are determined from solving the following linear equation:

\[
\begin{bmatrix}
PC1_i & PC2_i & PC3_i \\
PC1_m & PC2_m & PC3_m \\
PC1_f & PC2_f & PC3_f
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3
\end{bmatrix}
= \begin{bmatrix}
q_i - \bar{q} \\
q_m - \bar{q} \\
q_f - \bar{q}
\end{bmatrix}.
\]  

(2)

To solve Equation (2), \( q_i, q_m, \) and \( q_f \) are needed. \( t_i, t_m, t_f \) mean initial, middle, final time corresponding boundary conditions. We use discrete sensing data \( q_{E_i}, i = 1, \ldots, 4 \) at state transitions to determine the boundary conditions for the joint trajectory. The discretized boundary conditions (BCs) for the hip, knee \( q_i, q_m, q_f \) joints are stored as lookup values. For the currently sensed hip BC values (e.g., \( \{q_{E_i}, q_{E_m}, q_{E_f}\} \) in state S1-S2), we search the nearest hip BC value set and set the corresponding knee BC value. In this paper, we use 50 BC’s from arranging the captured sample motion data.

C. Assistive Torque Generation

When the event E1 (or E3) is detected, both swing leg (flexion) and stance leg (extension) assistive torques are planned with Catmull-Rom spline curves for the current step as in Fig. 3. The assistive torque profile is parameterized with assist peak location \( l_{peak} \), start location \( l_{start} \), peak duration \( d_{peak} \), descending duration \( d_{desc} \) and the peak torque value \( T_{peak} \) within a step cycle (i.e. an half of walking cycle) as in Fig. 6. The whole torque profiles can be shifted by the parameter of assist lag \( p_{lag} \).

\[ \text{Fig. 3. Finite state machine for walking motion modeling and its relation to assistive torque planning (bold/dashed line means joint torque for right/left hip).} \]

\[ \text{Fig. 6. Assistive torque profile parameterization.} \]

\[ \text{Fig. 7. Swing leg assist strategy.} \]

The assist peak location for swing leg assist is determined by searching the moment of the peak positive power of the previous opposite step motion. We estimate the moment of peak positive power by sensing the maximum joint acceleration. The assist start location for flexion assist is determined by the previous step’s opposite heel landing. We choose this strategy to quickly synchronize the interval of flexion assist to the positive work interval of the current swing. Figure 7 shows our assist strategy for hip flexion.

But the assist peak location for stance leg is dependent on the opposite leg’s swing leg assist lagging -10~10%. Notice that stance leg assist timing does not coincide with the biological positive power peak of the stance leg [17].
Unlike the case of a swing leg assist, the stance leg is already loaded with large torques. So the extension force could be unintentionally transferred to the torso (not thigh).

Before performing the steady-state walking, the assistive torque $\tau_{\text{assist}}$ in (3) is scaled down from the simple state-reward counter $n_{\text{stdy}}$. When a successive state change is achieved such as $S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_4 \rightarrow S_1$, we increase the counter value to the maximum six (we assume steady state walking is achieved at six successive state changes by observing the walking speed change for normal case, $n_{\text{stdy}} = 6$). The current walking parameters (speed, step length, step time) and their difference values are also used to reset or decrease the state-reward counter.

The desired control torques are described by the summation of the planned assistive torque and the compensation torques. The role of compensation torques is to improve control transparency (reducing impeding elements, e.g. inertia, gravity effects) of the wearable assist device.

$$\tau_{\text{des}} = \omega_1 \tau_{\text{assist}} + \omega_2 \tau_{\text{ff}} + \omega_3 \tau_{\text{fr}}$$  \hspace{1cm} (3)

where $\omega_1 = n_{\text{reward}}/n_{\text{stdy}}$ is a variable weighting factor for a scale-down assist, $\omega_2$ and $\omega_3$ are fixed and calibrated weighting factors ($\omega_2, \omega_3$ are manually tuned with zero assist), $\tau_{\text{ff}}$ is a feedforward compensation torque. The assist and compensation torques are planned by interpolating via points using spline curves as in Fig 3(b). The friction compensation torque $\tau_{\text{fr}}$ is

$$\tau_{\text{fr}} = \text{sign}(\dot{q})f_c + \mu_v \dot{q}$$  \hspace{1cm} (4)

where $f_c$ is a static friction torque, $\mu_v$ is a viscous friction coefficient.

D. Walking Regularity Enhancement

We use the measure for walking regularity as a stride time variability [18]. We can observe the increased stride time variability in elderly fallers (see [19], [20]). As children grow older, the stride time variability decreases (by a skilled motor control). Reversely, as elderly people become even older, the stride time variability increases (from a degenerative motor control). The weakened muscles and degenerated sensory nerves are one of the reasons [7] for increased stride time variability.

III. REAL EXPERIMENT

A. Detection of Walking Events with Only Hip Motion

We estimate the moment of heel landing using only hip motion data. So we validate the accuracy of detecting heel landing by comparing with actual heel landing time. Actual heel landing time can be sensed by observing the local peak of pelvis vertical acceleration. An IMU (Inertial Measure Unit) sensor attached at the pelvis is used for sensing vertical acceleration. The first plot in Fig. 8 shows the estimated heel landing times (state change: $S_5 \rightarrow S_6$ or $S_6 \rightarrow S_5$) coincide to the local peak of pelvis vertical acceleration. For the 50 heel landing during level walk at 2~3km/h speed, the mean of the error is 0.07±0.03s which is 4.58 percent error for each stride.

We can also see a successful state change for walking state recognition and appropriate assistive torque generation for the current walking state as shown in Fig. 9.

B. Walking Aid by Transferring Power from Assist Device to User

As a preliminary test to observe the effectiveness of walking effort-assist, we performed experiments on one healthy subject. We evaluate the walking effort-efficiency by measuring the heart rate.

The subject’s heart rate is measured at every 20 seconds with a heart rate sensor (H1, Polar Electro Inc.). Heart rate can be used for the simple estimation of energy cost during walking [21] (note that heart rate does not completely correspond to the metabolic cost). Treadmill walking is sequentially performed for the three different modes: 1) zero torque 2) assisted 3) free. Each trial lasts 15 minutes but the data during the first 5 minutes are not used to minimize transient effects. Zero torque means that the desired torque is set to zero (transparent mode). In assisted mode assistive torque is applied to the swing leg with 8 Nm peak torque and to the stance leg with 4 Nm peak torque. Free mode means walking without the device. Between the trials of each mode
TABLE I
MEAN AND STANDARD DEVIATION OF HEART RATE

<table>
<thead>
<tr>
<th>Condition</th>
<th>Standing</th>
<th>Walking</th>
<th>Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero torque</td>
<td>89.0±1.9</td>
<td>103.1±2.5</td>
<td>+14.1 (+15.8%)</td>
</tr>
<tr>
<td>Assisted</td>
<td>88.5±3.8</td>
<td>100.1±2.1</td>
<td>+11.6 (+13.1%)</td>
</tr>
<tr>
<td>Free</td>
<td>84.6±2.9</td>
<td>95.3±2.2</td>
<td>+10.8 (+12.7%)</td>
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</tbody>
</table>

Heart rate for 3km/h walking (bpm)

<table>
<thead>
<tr>
<th>Condition</th>
<th>Standing</th>
<th>Walking</th>
<th>Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero torque</td>
<td>91.5±2.6</td>
<td>116.0±1.9</td>
<td>+24.5 (+26.8%)</td>
</tr>
<tr>
<td>Assisted</td>
<td>92.5±2.3</td>
<td>109.4±1.9</td>
<td>+16.9 (+18.3%)</td>
</tr>
<tr>
<td>Free</td>
<td>88.5±3.3</td>
<td>105.7±3.2</td>
<td>+17.2 (+19.4%)</td>
</tr>
</tbody>
</table>

The subject was sufficiently rested (seated for 15 minutes). Before the trial of each mode, the heart rate of the subject is measured for 5 minutes to obtain the base line of the heart rate for standing.

Figure 10 and Table I show the result of heart rate for the different walking speeds (performed at different day). The results clearly show the reduced heart rate of 3~7 bpm for all cases between the zero torque mode and the assisted mode. But the heart rate of assisted walking is higher than free case (no wear). The main reason is due to the added mass and inertia by wearing the assist device. The weight of our prototype is about 4.6kg (not negligible). So the standing heart rate of free case is less than that of wearing cases by 4 bpm as shown in Table I. We expect a better performance with our next prototype which is expected to be lighter.

We also checked the relative variation of heart rate from each base line to minimize the effect of added mass. The heart rate variation for the assisted is similar (13.1%, 12.7%) or slightly lower (18.3%, 19.4%) than that of free walking at 2km/h, 3km/h speed as shown in Table I. If we sufficiently reduce the total mass of the system, we anticipate that it is possible to reduce the metabolic cost of assisted walking than that of free walking (notice that added mass and inertia more negatively affect the dynamic walking motion than just standing).

C. Walking Regularity Enhancement

Although reducing metabolic cost has not yet been clearly solved, walking aid is possible by power assisting weak muscle (e.g. preventing foot drop), or correcting wrong walking posture (e.g. enhancing walking regularity). Our assist planning is based on previous opposite step motion which allows us to effectively enhance the regularity of walking. We evaluate the walking periodicity (regularity) by measuring the stride time variability.

The subject’s stride time (successive two step time) is measured at every step with sensed state duration times. Treadmill walking is sequentially performed for the three different modes; 1) zero torque pre 2) assisted 3) zero torque post. Each trial lasts 3 minutes. Baseline walking motion is intentionally impeded by wearing the unassisted device (inertia and friction are occurred by the device) to emulate elderly irregular walker.

To check the stride time variability (STV), we use the measure of standard deviation (SD) and coefficient of variation (CV) of stride time. We also use the standard deviation of stride time change (SDc) to show walking regularity more clearly (see Fig. 11). Figure 12 and Table II show that our assist method has the immediate effect for walking regularity enhancement. SD is reduced by 42%, CV is reduced by 37%, and SDc is reduced by 61%. As shown in Fig. 13, the reduced stride time variability means that the assisted walking motion is more regular and symmetric. Although the subject is not an elderly faller, we validated that our assist method effectively reduce the stride time variability for irregular walking.

Fig. 11. Stride time and its change for 3km/h walking.

IV. Conclusion

We proposed an event-driven control for walking assist with hip mounted exoskeleton robots. For modeling user’s current walking motion, a novel finite state machine is constructed. We also developed a gait primitives based motion reconstruction method. Using those methods we estimated the moment of heel landing without a foot sensor. This makes it possible to achieve natural assist by driving appropriate assistive torques. Our assist method effectively enhanced walking regularity.
TABLE II

<table>
<thead>
<tr>
<th>Stride Time Variability for 2km/h walking</th>
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<tbody>
<tr>
<td>Index</td>
</tr>
<tr>
<td>SD (ms)</td>
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<tr>
<td>CV (%)</td>
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<tr>
<td>SDₐ (ms)</td>
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<tr>
<th>Stride Time Variability for 3km/h walking</th>
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<td>Index</td>
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<tr>
<td>SD (ms)</td>
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<td>CV (%)</td>
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<td>SDₐ (ms)</td>
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<th>Stride Time Variability for 4km/h walking</th>
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<td>Index</td>
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<tr>
<td>SD (ms)</td>
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<tr>
<td>CV (%)</td>
</tr>
<tr>
<td>SDₐ (ms)</td>
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</table>

Fig. 12. Stride time changes for different walking speeds. The box plots indicate the range of stride time changes. On each box, the central horizontal line is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually with cross marks.

References


Fig. 13. Stride time variability for different walking speeds.