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Functional Task based Assistance during Walking for a Lower Extremity Assistive Device

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***Abstract*—In this paper, we propose a functional task based assistance controller to aid user in the walking task with our Lower Extremity Assistive Device (LEAD). Firstly, a gait period detector, which utilizes a Gaussian Mixture Model (GMM), is developed to estimate the user's current gait period among the six major periods. Then, an impedance based controller is used to apply assistive torques to the hip and knee joints of the user based on the functional task intended at the current gait period. To validate the above control scheme, preliminary experiments have been performed with one healthy subject walking on a treadmill. The results show that the gait period detector can effectively detect each gait period for the whole cycle. Based on measurements of the heart rate, the proposed assistance method has shown that it can effectively assist a human user in walking at speed of $1\ km/h$.**

I. Introduction

Gait period detection method estimates the current motion period based on sensors worn on the user, and aims to inject an appropriate amount of force in the right direction to assist the user in that particular period of motion. Wearable gait period detection systems were developed initially as a less expensive alternative to traditional optical based clinical gait analysis systems [1]–[3]. These gait analysis systems can quantitatively analyze the gait of patients which offers the clinicians a tool for assessing gait pathologies as well as an evaluation tool in rehabilitation applications.

Currently, there are many lower extremity exoskeletons [4] and control strategies for assistance [5]. In this paper, we will only review some devices exploiting gait period detection method in order to provide timely assistance during the user's gait, for example the HAL and the MIT's exoskeleton.

The HAL broadly classifies walking into stance and swing states based on Ground Reaction Force (GRF) sensors threshold [6]. For the hip joint, constant predetermined flexion and extension assistive torques are activated based on the stance and swing states of the opposite leg. This requires sensors to be mounted on the unaffected leg, which unnecessarily encumbers its motion. For the knee joint, no assistive torque is provided during the swing state. However, users may require assistive force particularly at certain periods of swing where knee flexion is required for over ground clearance.

For MIT's exoskeleton [7], stance and swing state is subdivided into early and late phases. Maximum and minimum turning points of joint angles are used as transitions criteria within each subdivided state, making this method susceptible to noise. Moreover, the constant preset assistive torque used at the hip does not correlate well with the joint torque profile of a human during level walking. Similarly, the subdivision of the knee states was not exploited as only resistive force is added throughout the stance state while the joint remains free during all the subdivided swing states.

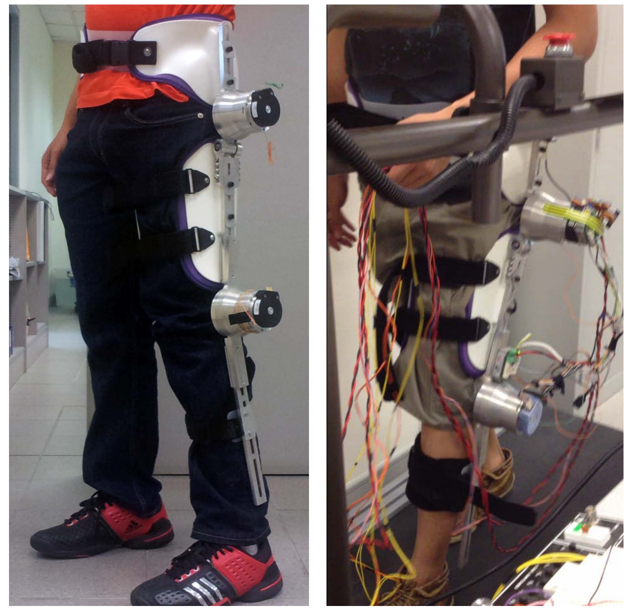

Fig. 1. Lower Extremity Assistive Device (LEAD)

We can see that current gait period detection method that provide assistance overly-simplifies the classification of gait periods. From the authors' knowledge, no research have tried to provide functional assistance in subdivided gait period while walking. Moreover, a single threshold for transition may lead to robustness issues in the presence of noise. Thus, in this paper, we propose a functional task based assistance controller to aid user during walking, and evaluate it with our Lower Extremity Assistive Device (LEAD), as shown in Fig. 1. The details of the device can be found in [8].

The paper is organized as follows. In Section II, we introduce the gait period detector using Gaussian Mixture Model and how to apply an assistive torque in each subdivided period . Then in Section III, the experiment details are given, and in Section IV, experimental results are shown and discussed. The last section provides the conclusions and future works.

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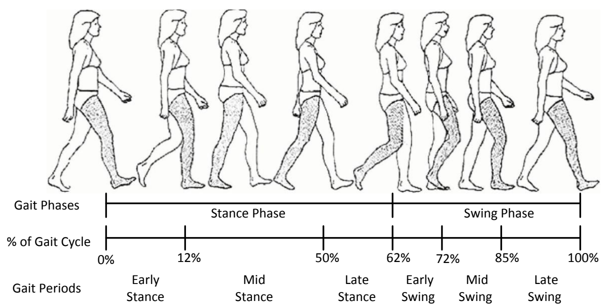

Fig. 2. Normal walk cycle illustrating the gait periods and their starting and ending percentage [9]

TABLE I
GAIT PERIODS AND FUNCTIONS

Gait Periods	Functions
Early Stance	Loading, weight transfer
Mid Stance	Support of entire body weight, center of mass moving forward
Late Stance	Unloading and preparing for swing
Early Swing	Foot clearance
Mid Swing	Limb advances in front of body
Late Swing	Limb deceleration, preparation for weight transfer

II. GAIT PERIOD BASED ASSISTANCE CONTROLLER

It is widely accepted that a basic human gait cycle during level walking could be generalized into a periodic sequence of events as shown in Fig. 2 [9], [10]. Different stages of the gait cycle, also known as gait periods, have different functional requirements as summarized in Table I. Therefore, we postulate that if the gait periods could be determined, the intended action of the joints would be known. As a result, the assistive device can provide required torque in the appropriate direction to aid the user during walking. For stroke patients, they could exhibit a more normal gait pattern with the help of our proposed controller.

To achieve this objective, two requirements must be met. Firstly, we must be able to detect the different periods and their transitions in a gait cycle. Next, we have to modulate the torque output to assist in the functional task of the user during each gait period.

A. Gait Period Detector using Gaussian Mixture Model (GMM)

The gait period detector attempts to divide the gait cycle into the six gait periods, namely, early stance, mid stance, late stance, early swing, mid swing and late swing. Since the gait cycle is repetitive, the gait periods of a healthy individual will transit sequentially during walking. If the sensor data are exactly the same during each gait cycle, a threshold method based on GRF and joint angles can effectively serve as transiting conditions between the states. However, the variability between each gait cycle makes such methods not as robust.

In a previous study, a Support Vector Machine (SVM) based gait period classification algorithm was developed [11]. The detection accuracy was high, but the high computational cost made it difficult to implement in realtime. Therefore in this work, we use a Gaussian Mixture Model (GMM) [12] to characterize the probability of the user in each gait period. The GMM classifier considers both the mean and covariance of the sensor data to model a multivariate Gaussian distribution [13] in order to evaluate its probability in each state. Moreover, its level of complexity could be controlled based on the number of mixture components defined by the designer. For real-time applications, a small number of mixture components could be used to achieve fast computational speed.

A GMM is constructed for each gait period. From [12], the probability of being in a gait period λ, for a given set of D-dimensional sensor measurement x, is written as

$$p(x|\lambda) = \sum_{i=1}^{M} \omega_i g(x|\mu_i, C_i) \tag{1}$$

where $w_i, i = 1, \cdots, M$, are the mixture weights for the GMM, and $g(x|\mu_i, C_i)$, $i = 1, \cdots, M$, are the component Gaussian densities for the GMM. Each component density is a D-variate Gaussian function of the form

$$g(x|\mu_i, C_i) = \frac{1}{((2\pi)^{D/2}|C_i|^{1/2})}\ exp\{-\frac{1}{2}(x-\mu_i)'C_i^{-1}(x-\mu_i)\} \tag{2}$$

where μ_i and C_i are the mean vector and covariance matrix, respectively. The mixture weights satisfy the constraint of $\Sigma_{i=1}^{M}\omega_i = 1$.

Each GMM is parameterized by the mean vectors, covariance matrices and mixture weights from all component densities, given as

$$\lambda = \{\omega_i, \mu_i, C_i\}, \quad i = 1, ..., M \tag{3}$$

Given the training data and GMM configuration, the Expectation Maximization (EM) [14] algorithm is used to find the Maximum Likelihood (ML) estimates of the parameters of each GMM.

Once each GMM is parameterized, the current gait period for a given input of sensor measurement x, is the gait period with the highest probability during stance or swing respectively.

B. Functional Assistive Torque

After the gait period is determined, an assistive torque could be applied in a manner that helps the user achieve the joint's intended function in that specific gait period. In this work, an impedance-based method [15] is used to generate the assistive torque. The torque of each joint can be modulated with an impedance property which consists of a spring and damper characteristic with a fixed equilibrium position. A different set of impedance property will be used at different periods of the gait cycle. This method differs from

TABLE II
DIRECTION OF ASSISTIVE TORQUE OF JOINTS FOR EACH GAIT PERIOD

No.	Gait Periods	Direction of Assistive Torque at Joint	
		Hip	Knee
1	Early Stance	Extension	Extension
2	Mid Stance	Neutral	Extension
3	Late Stance	Flexion	Neutral
4	Early Swing	Flexion	Flexion
5	Mid Swing	Neutral	Neutral
6	Late Swing	Extension	Extension

traditional rehabilitation robots which are mostly position controlled. In position control, the joints are controlled to track a predefined trajectory for every step. The lack of cycle to cycle variation in kinematics and sensorimotor feedback limits motor learning [16]. Hence, over the years, researchers have tried to make the system more compliant by incorporating impedance control to their predefined trajectory in order to increase patient's activity [17]–[19]. For these compliant trajectory methods, assistive torque will be felt by the user if he lags the predefined trajectory of the equilibrium point. However, resistive torque will be felt if the user moves faster than the equilibrium point. Thus, those patients who are capable of accomplishing some functional tasks on their own will find themselves hindered by the device. Therefore, the approach used in this work aims to provide assistive torque to assist in the intended function only in the intended direction at each gait period. In this way, the impaired functional tasks will be supported by the device, while freedom of motion will be given to the patient for those unimpaired tasks.

Based on the gait analysis in [9], the direction of assistive torque at each joint within each gait period can be determined, as shown in Table II.

The unidirectional impedance model of each joint is given by

$$\tau = k(\theta - \theta_0) - b\dot{\theta} \tag{4}$$

where the joint torque τ, is related to the input joint angular position θ, and speed $\dot{\theta}$, by the stiffness term k, damping term b, and equilibrium angle θ_0. If the direction of assistance is in extension, the assistive joint torque is zero if the computed τ is less than zero. And for joint in flexion, the assistive torque is zero if the computed τ is greater than zero. The assistive torque for joints in neutral mode is set to be zero.

As switching between the gait periods may result in abrupt switching of assistive torque, a sigmoid function was added during each transition to fade away the previous torque while fading in the desired assistive torque at its current state.

The sigmoid function is described by

$$y = \frac{1}{1 + exp\{-A(t - T)\}} \tag{5}$$

where t is the time elapsed since transition, and A and T are parameters to adjust the steepness and time shift of the function, respectively. Fig. 3 shows the output of the sigmoid function implemented, where parameters A and T are set to be 50 and 0.1, respectively.

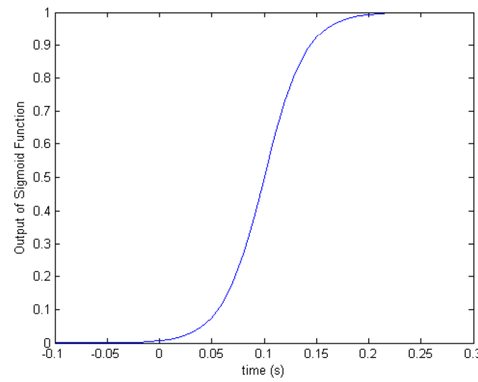

Fig. 3. Sigmoid function used to smooth the torque profile

Hence the output torque with the sigmoid fading will be

$$\tau_{output} = (1 - y)\tau_{prev} + y\tau_{curr} \tag{6}$$

where τ_{prev} is the assistive torque from the previous gait period just before the transition and τ_{curr} is the assistive torque in the current gait period.

III. EXPERIMENTS

A. Gait Period Detector using Gaussian Mixture Model (GMM)

To parameterize each GMM, training data have to be collected. Therefore, the LEAD is worn by a able-bodied subject who is then asked to walk on a treadmill at a speed of 1 km/h with the LEAD. The walking speed is selected to be comparable to the walking speed of stroke patients [20]. The subject is a healthy 28-year-old male, 63 kg in weight, 1.71 m in height. The joint angle of the LEAD is first initialized to be zero when that subject is in an upright standing posture before each walking trial. Prior to the data collection, the subject is given five minutes to walk on a treadmill while wearing the LEAD in friction compensation mode to get used to the assistive device.

Five sensor measurements are recorded and represented by a 5×1 vector x. The first two are the hip and knee flexion angles of the LEAD respectively. The remaining three measurements are the GRF readings from the first and fourth metatarsal, and the calcaneus positions, which will be referred to as front, mid and back GRF, respectively. All readings are captured at a rate of 500 Hz.

A total of three walking trials are conducted with five minutes of rest between the trials. For each trial, the treadmill speed is set to 1 km/h, and the data are recorded only when the subject reaches a steady walking speed. Thirty seconds of readings are recorded for each trial.

Before training, the measurements from each sensor are normalized based on the respective maximum and minimum values for all the walking trials. The time span of the data is normalized in terms of percentage of gait cycle, which is computed based on the time period across two consecutive heel strike events.

The training label for each gait period is based on their respective occurrence in terms of percentage gait cycle from a normal Clinical Gait Analysis (CGA) data in Fig. 2 [9]. Once parameterized, the GMM is implemented on the LEAD for on-line classifications.

B. Functional Assistive Torque

The gait period detector is implemented on the LEAD, before the functional assistive torque model is incorporated. Before the start of the experiment, the subject is given two minutes to walk on a treadmill at $1\ km/h$ while wearing the LEAD to familiarize with the assistive device.

To tune the impedance parameters, the subject is asked to walk on the treadmill at $1\ km/h$ with the LEAD in assistance mode. The equilibrium points are pre-set and the stiffness and damping parameters are adjusted for each gait period until the subject feels a comfortable assistance for the entire gait cycle. Pre-set equilibrium points for the hip are chosen based on the average maximum and minimum hip trajectory during un-assisted walking and the intended direction of assistance. Equilibrium points for the knee are chosen based using similar method with the exception of the early stance and mid stance. For early stance and mid stance, a hyperextension equilibrium point of -5 degree is chosen to produce an overall extension torque during full extension to prevent the buckling of knee during load bearing. To ease in the calibration process, the damping parameter is set to be one-tenth of the stiffness parameter, leaving only a stiffness parameter to be tuned for each period. The entire calibration process took about three minutes.

Next to determine whether or not the LEAD is providing assistance, the subject is asked to perform a walking trial on the treadmill at $1\ km/h$ in each of the following conditions:

1) Unassisted
2) Assisted
3) Free

In the unassisted mode, the subject wears the LEAD with only friction compensation for harmonic actuator [21] implemented. Under the assisted condition, the subject wears the LEAD with both the friction compensation and functional assistive torque implemented. The free condition serves as a control, where the subject walks without wearing the LEAD.

Each walking trial lasts 15 minutes. The subject's heart rate is measured at every 30 seconds interval with a heart rate sensor (MN-01, Pulse Plus) as heart rate has been found to be an accurate estimate of energy expenditure during steady-state sub-maximal work in normal and disabled adults engaged in walking [22]. A rest period of 30 minutes is given to the subject before the start of each trial to ensure sufficient time for the heart rate to return to baseline. To determine the resting heart rate, before the start of the first trial, the subject is seated and the heartbeat is measured for every 30 seconds over a period of 5 minutes.

TABLE III
AVERAGE TRANSITION PERCENTAGES FOR GAIT PERIOD DETECTOR

Period Transition	Transition of Typical CGA (%)	Average Estimated Transition (%)
1 to 2	12	17.2 ± 4.03
2 to 3	50	50.3 ± 2.69
3 to 4	62	60.0 ± 3.87
4 to 5	75	72.7 ± 4.04
5 to 6	85	87.3 ± 2.30

TABLE IV
IMPEDANCE PARAMETERS

Gait Period	$k(Nm/rad)$		$b(Nm/rad\ s^{-1})$		$\theta_0(rad)$	
	Hip	Knee	Hip	Knee	Hip	Knee
Early Stance	22.9	11.5	2.3	1.1	0.0	-0.087
Mid Stance	0.0	22.9	0.0	2.3	0.0	-0.087
Late Stance	22.9	0.0	2.3	0.0	0.524	0.0
Early Swing	22.9	22.9	2.3	2.3	0.524	0.873
Mid Swing	0.0	0.0	0.0	0.0	0.0	0.0
Late Swing	22.9	11.5	2.3	1.1	0.0	0.0

The control loop and data capturing rate of the LEAD is set at $250\ Hz$ for the above assisted trials.

IV. RESULTS AND DISCUSSIONS

To validate the performance of the gait period detector, the estimated period transition was normalized in terms of percentage gait cycle and compared with the transition from CGA studies done in [9], as shown in Table III. Average estimated transition was found to be close to the typical CGA transitions, with less than 5% deviation on average.

Table IV shows the calibrated impedance parameters for each gait period. These parameters are implemented during the assisted walking trial.

A segment of the data recorded during the assisted walking trial is shown in Fig. 4. The top graph shows the gait period found by the gait period detector. It is observed that the gait period detector can effectively detect each gait period and the gait periods transit sequentially in increasing order. However, transitions to mid stance are skipped in 20.0% of the gait cycles recorded. In these gait cycles, the gait period detector transits from early stance to late stance directly. Nonetheless, subject remains comfortable with the assistance provided.

The second and third graphs indicate the joint angles and GRF respectively. Generally, the data are periodic with minor cycle-to-cycle variation. When compared to unassisted condition, the trajectory of the hip is not as smooth especially during periods with addition of assistive torque. This is attributed to the compliant of the attachment between the user and device. Since the user is mainly pushing the device during periods without assistive torques, while the addition of assistive torque makes the device push the user instead.

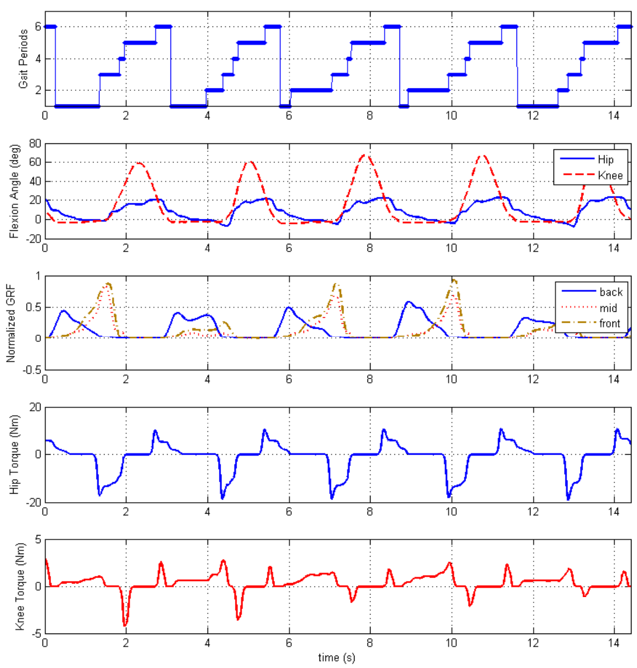

Fig. 4. Estimated gait periods, sensors information and joint torque of a user during 1 km/h walking with LEAD in assisted mode. (Gait periods are labeled as follows, Early Stance = 1, Mid Stance = 2, Late Stance = 3, Early Swing = 4, Mid Swing = 5 and Late Swing = 6)

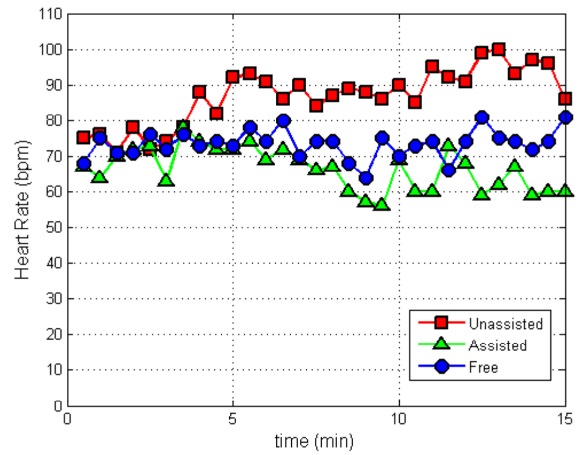

Fig. 5. Heart rate, in terms of beats per minute (bpm), during walking trials under different conditions

TABLE V
AVERAGE AND STANDARD DEVIATION OF HEART RATE

Condition	Heart Rate (bpm)
Unassisted	90.9 ± 4.7
Assisted	64.4 ± 5.6
Free	73.6 ± 4.5
Baseline	62.8 ± 2.0

The last two graphs show the assistive torque provided by the LEAD at the hip and knee joint. The assistive torques are continuous and smooth. It can be seen that the LEAD generate flexion and extension torques at the hip appropriately based on the gait period detector. Peak flexion and extension assistive torque of the hip averages about 18 Nm and 10 Nm respectively. These correspond to 35.7% and 19.8% of the respective peak hip flexion and extension torque of the subject during normal level walking based on the subject's weight and CGA data. Assistive flexion and extension torque at the knee could also be observed to aid in walking. From the graph, assistive flexion torque at the knee could be seen during early swing to aid in the subject's knee flexion. Moreover, an overall extension torque is generated during early stance and mid stance which aids the subject in weight bearing.

Fig. 5 shows the change of the subject's heart rate with time under each of the three conditions. In the first three minutes, the heart rates for all three conditions are quite similar. After which, the heart rate of the unassisted condition starts to increase and stabilize after five minutes of walking. The heart rate under the free condition appears to be relatively flat with a gentle upward slope throughout the entire walking trial. In the assisted condition, the heart rates remain similar to the free condition until about seven minutes, when the heart rate starts decreasing and stabilizes at a lower rate after nine minutes of walking.

Table V lists the average and standard deviation of heart rate under different conditions. Only the heart rates after the first five minutes are taken for the walking trials to eliminate transient effects. The baseline heart rate was measured to be 62.8 bpm during the five minutes of rest.

The heart rate of walking under unassisted condition is found to be significantly higher ($p < 0.05$) than the heart rate of walking under the free condition. This is not unexpected, since the LEAD adds additional weight to the leg, and it was found that net metabolic rate during walking increased with leg-load magnitude and more distal leg-load location [23].

The heart rate of walking under assisted condition is found to be significantly lower ($p < 0.05$) than the heart rate of walking under the unassisted condition. This indicates that the user benefits from proposed controller in walking, as less effort is required to walk compared with the unassisted case.

Interestingly, the heart rate of walking under assisted condition is also found to be significantly lower ($p < 0.05$) than the heart rate of walking in the free condition. The MIT quasi-passive exoskeleton found an increase metabolism of 32% during assisted walking as compared to control [24]. In [25], a 60% increase of energy consumption was found when a prototype exoskeleton (EXO) was worn as compared with the control condition. However, it is premature to conclude that the walking with LEAD using the proposed method is beneficial over free walking. Most notably, the walking trials in this study are at limited to 1 km/h, which is well below the average walking speed of 5 km/h [26]. Free walking with speeds less than the individual preferred walking speed lead to higher energy consumption [27]. Nonetheless, the LEAD under the proposed method has preliminarily shown that it can effectively assist this subject in walking at speed of 1 km/h.

Please note that this is only a pilot study to test the feasibility of the proposed controller. A larger study involving more healthy subjects is currently being conducted. Concerning its application for stroke rehabilitation, more studies needs to be done on how the modified gait of stroke patient will affect the results of the gait period detector.

V. Conclusions and Future Works

In this paper, we first propose to provide functional task assistance in subdivided gait periods during walking with the lower extremity assistive device. A gait period detector as well as assistance controller are introduced in details. The proposed controller is validated via a healthy subject experiment walking on treadmill, and the heart rate results show it can assist the user effectively at speed of 1 km/h. In the near future, we will evaluate the proposed assistance controller with more healthy subjects as well as in gait rehabilitation of stroke patients.

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