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# Model-based Fuzzy Adaptation for Control of a Lower Extremity Rehabilitation Exoskeleton

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**Abstract— Different gait patterns of stroke patients cannot be derived satisfactorily by traditional treadmill training robots. This paper presents a method to generate adaptive trajectories for controlling a lower extremity rehabilitation exoskeleton designed to help patients recover or improve walking ability. The model-based adaptation mechanism that consists of an inverse dynamic model, a trajectory generator and a fuzzy adaptation algorithm is proposed to minimize patient's discomfort when active muscle contractions are not easily to be obtained. The effectiveness of the fuzzy adaptation algorithm, which accounts for the experience of a rehabilitation doctor, is demonstrated numerically with an illustrative example in this paper.**

**Index Terms – Lower extremity model, fuzzy adaptation, rehabilitation, exoskeleton, gait recovery, treadmill training**

## I. INTRODUCTION

Manual locomotor training of a patient without normal walking ability is often tedious, and its effectiveness generally depends on the experience of the therapist. Rapid advances in mechatronics and robotics have motivated a flurry of research, in the last five years or so, on lower extremity exoskeletons (or orthoses) to assist the rehabilitation process.

Treadmill training is one of the most common means of rehabilitation processes. Among them, the Lokomat (Hocoma, Swaziland) [1]-[2] is one commercialized gait training devices, which has actuated hip and knee joint. The AutoAmbulator [3] is a similar treadmill device to help patient restore normal gait. In a typical training process, the body weight of the patient is supported while his lower extremities are guided by two pairs of robot legs following a gait reference. These devices are shown to be effective in improving the walking ability in incomplete (spinal cord injured) SCI patients, but they are not likely to be the universal solution for all patients, due to the less-challenging locomotor tasks [4]. Some novel treadmill training methods have also been reported recently. The exoskeleton called LOPES created by Veneman *et al.* [5] was designed using cable transmission. Gravity balancing leg orthosis (GBO) developed at University of Delaware can alter the level of gravity load at a joint without power supply [6].

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Another branch of rehabilitation devices is assistive orthoses. They are mainly designed to prompt motor learning by combination of adding or dissipating power at the human joint while walking. MIT Ankle-Foot Orthosis is an impedance variable device to assist dropfoot gait [7]. Sawichi *et al.* [8] and Beyl *et al*. [9] have proposed a different actuating way based on pneumatic power. Compared with treadmill training, assistive orthoses are more portable, but they may face more problems in multiple environments as well.

Most rehabilitation devices are designed according to the three motor learning principles, i.e. practice, specificity and effort [4]. More and more researchers are now trying to execute specific task and involve patient's participation in their rehabilitation. As to the treadmill robots, existing designs, however, are mainly passive in nature in the sense that patients when feel uncomfortable cannot change their gait. There is a need for an exoskeleton design that facilitates collaboration and communication between physiologists and research engineers so that human locomotion physiology can be accommodated. Jezernik *et al*. ([10]-[11]) proposed an adaptation algorithm (based on parameterized gait description and optimization) for Lokomat to solve the problem between standard trajectory and individual walking pattern, which however, may not guarantee a satisfactory result in practice nor adapt to a broad trajectory due to the limitation of merely three parameters (amplitude, period and vertical deviation constant). On the other hand, Banala *et al.* proposed a force field scheme for safe and effective training, under which patients can develop their own gait pattern with certain assistance as they need [12]. Kiguchi *et al*. have succeeded in applying neuron-fuzzy controller in designing a EMG signal based exoskeleton. It is reported to be able to adapt to different user flexibly [13].

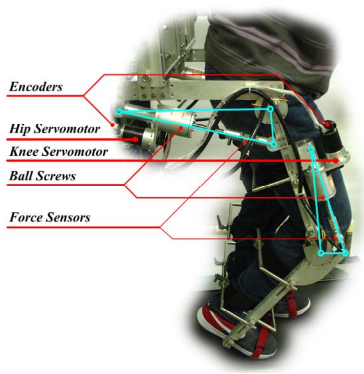
This paper has been motivated by the interests to develop an adaptive exoskeleton system that takes into account the experience of a rehabilitation doctor in implementing a training strategy, and involves patients in controlling their own rehabilitation. The remainder of this paper offers the followings:

- We offer a model-based adaptation method, which consists of a trajectory generator, an inverse dynamic model that estimates the active torque of the patient, and a fuzzy adaptation algorithm, for specifying an adaptive reference trajectory of a lower extremity rehabilitation exoskeleton. The focus here is to derive adaptive trajectories to help gait patients gain or regain normal gaits while minimizing the active torque exerted by the patient during training.

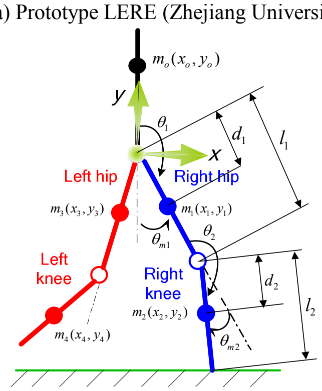
- We present an inverse dynamic model of the rehabilitation exoskeleton, which provides a useful alternative to estimate the active torque of the patient (when active muscle contractions are not easily available) and hence any possible patient discomfort during gait training.
- We formulate an adaptive algorithm based on fuzzy linguistic logics to implement the training strategy and account for the experience of a rehabilitation doctor. The effectiveness of the fuzzy adaptation algorithm has been demonstrated numerically with an illustrative example.

## II. Overview of the Model-Based Adaptation (MBA)

The model considered here is a four-DOF wearable lower extremity rehabilitation exoskeleton (LERE) similar to Lokomat [1]. Fig. 1(a) shows an example LERE developed at Zhejiang University, which has two pairs of (right and left) hip and knee joints. Each joint has one-DOF in the sagittal plane, and is independently driven by a servomotor/ball-screw assembly complete with an encoder and a force sensor for measuring its angular displacement and driving torque respectively. The joint angular displacement can be calculated from geometry; or more specifically, from the properties of a triangle formed by a screw, thigh/shank rod, and support rod as illustrated in Fig. 1(a). Similarly, the joint driving torques can be computed from forces measured by two force sensors between the screw and hinge on the thigh/shank rod. The training speed/time and reference gait pattern are set in advance.




(a) Prototype LERE (Zhejiang University)




(b) Five-link human model

Fig. 1 Wearable lower extremity rehabilitation exoskeleton

### A. Lower Extremity Representation

Schematically, the patient is represented by a five-link bipedal walking model as shown in Fig. 1(b), where XY is the reference frame assigned at the end of the torso between the thighs. Using the lumped-parameter approach, the gravitational centers of right thigh and shank (with masses $m_1$ and $m_2$) are denoted as $(x_1, y_1)$ and $(x_2, y_2)$ respectively as shown in Fig. 1(b) where $l_i$ denotes the length of the $i^{\text{th}}$ limb; $I_i$ is its moment of inertia; $d_{i+1}$ is the distance between the gravitational center of the $i+1^{\text{th}}$ limb and the $i^{\text{th}}$ joint; and $\theta_i$ and $\theta_{mi}$ ($i = 1, 2$ or $3, 4$) are the generalized coordinates and measured angles respectively.

### B. Model-based Trajectory Adaptation

Fig. 2 illustrates the MBA mechanism for specifying an adaptive reference trajectory to the patient-exoskeleton system designed to eliminate any possible patient discomfort during gait training. We assume that the closed-loop angular position servos are stable and well-tuned; the focus here to derive an adaptive trajectory $\boldsymbol{\theta}_{\mathbf{r}}(t)$ is to help the patient gain or regain normal gaits while minimizing the active torque exerted by the patient during training.

The MBA mechanism consists of the following components:

- a position-velocity-time (PVT) trajectory generator,
- an lower extremity inverse dynamic model, and
- a fuzzy adaptation algorithm.

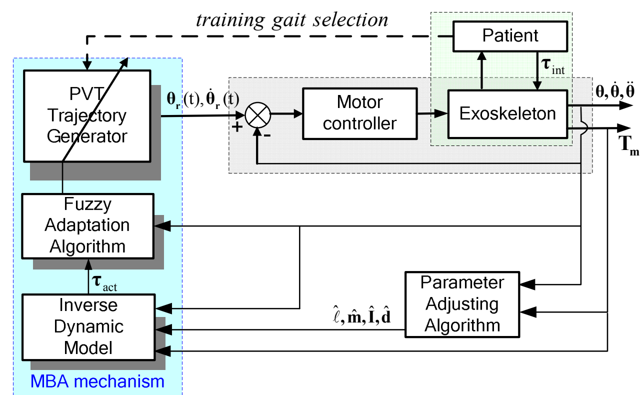



Fig. 2 Schematics illustrating model-based adaptation

<u>*Patient Gait Representation*</u>

In the PVT generator, trajectories are specified in real-time as reference inputs to the position servos of the exoskeleton. The PVT trajectory must satisfy the following criteria:

The angular positions are represented by discrete control points (CPs) to preserve the characteristic of the current gait at a sampling rate of 50Hz.

- The control points form a continuous sequence with smooth acceleration; otherwise, the exoskeleton could vibrate causing the patient to feel uncomfortable.
- The walking pattern of a patient is periodic. The trajectory must be generated such that the two endpoints of a complete trajectory cycle must be the same.

To meet the above criteria, each reference angular displacement $\boldsymbol{\theta}_{\mathrm{r}}(t)$ is characterized using a Fourier series. Since the training trajectory is periodic and complies with Dirichlet condition, it always converges. In discrete form, the fitting function is given in (1):

$$s_j = \sum_{k=1}^{K} a_k \sin(2\pi k \frac{jT_s}{T} + c_k) + b_0 \quad (1a)$$

$$\dot{s}_j = \frac{2\pi}{T} \sum_{k=1}^{K} a_k k \cos(2\pi k \frac{jT_s}{T} + c_k) \quad (1b)$$

$$\ddot{s}_j = -\left(\frac{2\pi}{T}\right)^2 \sum_{k=1}^{K} a_k k^2 \sin(2\pi k \frac{jT_s}{T} + c_k) \quad (1c)$$

where $k$=1, 2, …, $K$; $j$=0, 1, 2, …; and $T_s$ and $T$ are the sampling period and the gait cycle time respectively. The parameters ($a_k$ $b_0$ and $c_k$) in (1a-c) can be determined by minimizing (2) using a nonlinear least square method:

$$\|\delta\|_2^2 = \sum_{i=0}^{m} \left(s_j - \theta_{rj}\right)^2 \quad (2)$$

where $s_j$ is the CP angular position value at the $j^{\text{th}}$ time instant. For synchronized two-leg walking, the phase difference between the left and right legs is half a gait cycle $T$, or

$$\theta_{r-left}(t) = \theta_{r-right}[t + (2j+1)T/2] \quad (3)$$

<u>*Reference Trajectory Correction*</u>

As shown in Fig. 2, the MBA mechanism takes advantages of the measured trajectory along with the basic patient information (such as weight, height, age, gender, *etc.*) to estimate the following parameters characterizing the human-machine model:

$$\hat{\ell} = \begin{bmatrix} l_1 \\ l_2 \end{bmatrix}; \ \hat{\mathbf{m}} = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix}, \hat{\mathbf{I}} = \begin{bmatrix} I_1 \\ I_2 \end{bmatrix}, \text{ and } \hat{\mathbf{d}} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}.$$

With the adjusted model parameters and measured displacement and torque data of the exoskeleton, the active torque $\boldsymbol{\tau}_{act}$ through active muscle contractions of the patient can be estimated from the inverse dynamic model. Since the walking pattern is typically periodic, the computed active torque helps predict the patient's inclination to change the gait (magnitude and direction) in the next walking cycle.

As will be discussed, the inverse dynamic model provides a basis for the fuzzy adaptation algorithm that modifies the standard PVT trajectory to accommodate different walking patterns of the patient while approaching the normal gait boundary to avoid ill-developed trajectory.

## III. INVERSE DYNAMIC MODEL

Design analysis and real-time applications of the exoskeleton require both the forward and inverse dynamic models. Unlike *the forward dynamic model* which analyzes the trajectory for the given torques acting on the patient-exoskeleton during design, the inverse dynamic model is typically computed in real time. The *inverse dynamic model* defined here predicts the active torque $\tau_{act}$ (through active muscle contractions of the patient) for a given gait trajectory. The following assumptions are made in the model:

a) The lower extremity of a typical human subject is symmetric about the sagittal plane; thus, only the right lower limbs (denoted by $i$ = 1, 2) will be described.

b) During gait training, the patient's torso is suspended. The torso motion and interaction between two legs are neglected.

### A. Kinematic and Dynamic Equations

As shown in Fig. 1(b), $\theta_i$ and $\theta_{mi}$ ($i$ = 1, 2) are the generalized coordinates and measured angles respectively. For each leg, the relationship between the position vectors $\boldsymbol{\theta}_\mathbf{m} = [\theta_{m1} \quad \theta_{m2}]^\text{T}$ and $\boldsymbol{\theta} = [\theta_1 \quad \theta_2]^\text{T}$ is given by (4):

$$\boldsymbol{\theta}_\mathbf{m} = [\mathbf{R}]\boldsymbol{\theta} + \boldsymbol{\varphi}, \text{ where } [\mathbf{R}] = \begin{bmatrix} -1 & 0 \\ -1 & 1 \end{bmatrix} \text{ and } \boldsymbol{\varphi} = \begin{bmatrix} \pi \\ 0 \end{bmatrix} \quad (4)$$

Similarly, the measured torque $\mathbf{T}_\mathbf{m} = [\tau_{m1} \quad \tau_{m2}]^\text{T}$ can be expressed in the generalized (joint) coordinates in (5):

$$\mathbf{T}_{\boldsymbol{\theta}} = [\tau_1 \quad \tau_2]^\text{T} = [\mathbf{R}]^T \mathbf{T}_\mathbf{m} \quad (5)$$

where $\tau_i = \sum_j \tau_{mj} \frac{\partial \theta_{mj}}{\partial \theta_i} = \sum_j \tau_{mj} R_{ji}$ .

The dynamic model of the patient-exoskeleton system has the following form:

$$\mathbf{M}(\boldsymbol{\theta})\ddot{\boldsymbol{\theta}} + \mathbf{C}(\boldsymbol{\theta}, \dot{\boldsymbol{\theta}}) + \mathbf{G}(\boldsymbol{\theta}) = \boldsymbol{\tau}_\mathbf{m} - \boldsymbol{\tau}_\mathbf{f} - \boldsymbol{\tau}_\mathbf{T} + \boldsymbol{\tau}_{act} \quad (6)$$

$$\mathbf{M}(\theta) = \begin{bmatrix} m_1 d_1^2 + I_1 + m_2 l_1^2 & m_2 l_1 d_2 \cos(\theta_1 - \theta_2) \\ m_2 l_1 d_2 \cos(\theta_1 - \theta_2) & m_2 d_2^2 + I_2 \end{bmatrix}$$

$$\mathbf{C}(\theta, \dot{\theta}) = \begin{bmatrix} 0 & m_2 l_1 d_2 \dot{\theta}_2 \sin(\theta_1 - \theta_2) \\ -m_2 l_1 d_2 \dot{\theta}_1 \sin(\theta_1 - \theta_2) & 0 \end{bmatrix}$$

$$\mathbf{G}(\theta) = \begin{bmatrix} -(m_1 d_1 + m_2 l_1) g \sin\theta_1 \\ -m_2 d_2 g \sin\theta_2 \end{bmatrix}; \text{ and } \boldsymbol{\tau}_T(\theta) = \begin{bmatrix} F_N l_1 \sin\theta_1 \\ F_N l_2 \sin\theta_2 \end{bmatrix}$$

In (6), $m_i = m_{ie} + m_{ip}$ ; $I_i = I_{ie} + I_{ip}$ ; and the subscripts "$p$" and "$e$" denote the patient and exoskeleton respectively. In (6), the actuating torque $\boldsymbol{\tau}_\mathbf{m}$ supplied by the drive motors must balance the joint friction $\boldsymbol{\tau}_\mathbf{f}$, the torque $\boldsymbol{\tau}_\mathbf{T}$ due to the reaction force $F_N$ acting on the supporting leg by the treadmill, and the active torque $\boldsymbol{\tau}_{act}$ produced by the patient through muscle contractions which is assumed to represent the comfort level directly.

### B. Model Validation

Since active muscle contractions are not available for direct $\tau_{act}$ measurements, experiments were performed with a passive healthy subject on the prototype LERE shown in Fig. 1(a) to validate (6) for the inverse dynamic model. Numerical values characterizing the LERE, along with data characterizing human inertia properties [17], are summarized in Table 1.

TABLE 1: PARAMETERS FOR SIMULATION

| | Symbols | Thigh$_p$ ($i$=1) | Thigh$_e$ ($i$=1) | Shank$_p$ ($i$=2) | Shank$_e$ ($i$=2) |
|---|---|---|---|---|---|
| Length (m) | $l_i$ | 0.39 | 0.39 | 0.50 | 0.50 |
| Mass (kg) | $m_i$ | 9.52 | 1.43 | 4.48 | 1.82 |
| Inertia (kg.m$^2$) | $I_i$ | 0.14 | 0.02 | 0.09 | 0.04 |
| Center of mass (m) | $d_i$ | 0.20 | 0.20 | 0.29 | 0.29 |

In this experiment, a sequence of angular displacements and actuating torques at the left hip and knee joints of the LERE was experimentally recorded. Neglecting friction and the treadmill reaction acting on the supporting leg, the actuating torques at the knee and hip joints were computed from (6) with the measured hip and knee trajectory as shown in Fig. 3. The theoretical predictions are compared against experimentally obtained torque measurements in Fig. 4, which agree in general. Some discrepancies may attribute to both the mechanical system and the human subject:

– From the exoskeleton/treadmill system, errors are primary due to friction in the mechanical joints since the patient is passive and supported by the torso.
– From the subject, two likely factors are the parameter and gait differences between the standard data and test subject, and the potentially unaccountable intermingling active torque.

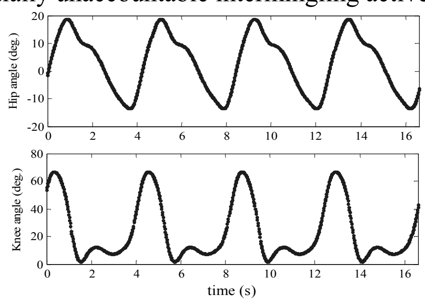



Fig. 3 Measured left hip and knee joint angles, $\theta_{m1}$ and $\theta_{m2}$

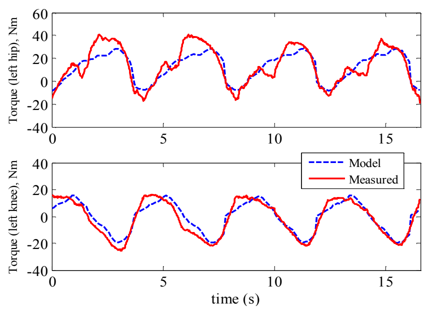



Fig. 4 Comparisons between inverse dynamic model and measured torques

## IV. Fuzzy Adaptation Algorithm

In order to take into account the experience of a rehabilitation doctor, the training strategy is implemented using an adaptive algorithm based on fuzzy linguistic logics. The adaptation algorithm modifies the pre-stored trajectory in the form of control points, which are referred to here as *initial reference trajectory* derived from gait pattern database of similar but healthy subjects. The adaptation algorithm adds its output to the discrete control points in the PVT trajectory generator. The function of the fuzzy adaptation algorithm is twofold:

– Establish an experiential mapping from the active torque τact derived from the inverse human-exoskeleton model to the deviations $\Delta s_j$ needed on the control points of the trajectory.
– Constrain the adjusting zone based on the training performance within an upper and a lower boundaries (denoted as $\hat{\theta}$ and $\underset{\smile}{\theta}$ respectively) of the normal gait.

To accommodate different patients, we normalize the two inputs to the fuzzy adaptation algorithm so that its output (or the deviation $\Delta s_j$) is kept within bounds as follows:

– An "adjusting margin" $\eta_j \in [0,1]$ is defined in (7):

$$\eta_j = \begin{cases} (1-\theta_+)/(1-\theta_\pm) & \text{if } \tau_{act} > 0 \text{ and } \theta_+ < 1 \\ (\theta_+ - \theta_\pm)/(1-\theta_\pm) & \text{if } \tau_{act} < 0 \text{ and } \theta_+ > \theta_\pm \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where $\theta_+ = \theta_r(j)/\hat{\theta}(j)$; and $\theta_\pm = \underset{\smile}{\theta}(j)/\hat{\theta}(j)$.

– Another factor influencing the adaptation is the normalized active torque $\tau_N(j)$ corresponding to $\theta_r(j)$ defined in (8):

$$\tau_N = \min\{\tau_{act}/\tau_0,\ 1\} \quad (8)$$

where $\tau_0$ is a default upper boundary of the active torque.

In (7), a larger adjusting margin implies that more trajectory deviation can be made. To avoid oscillations around and over the boundary, the adjusting margin is set to zero when the current trajectory is out of bound; no further adjustment is needed at this point while the doctor is being informed (of the adjusting margin, active torque and hip-knee angle-relationship) through the control interface**.** The default torque boundary $\tau_0$ in (8) can be determined from the experiments performed on a range of different patients.

### A. Fuzzy Rule-based Adaptation

The adaptation rules can be formulated with the help of a rehabilitation doctor. The normalized input variables $\eta$ and $\tau_N$ and the corresponding adjustment magnitude $|\Delta s_j|$ (or the output of the fuzzy adaptation algorithm) are characterized the fuzzy sets of the following linguistic values in (9a-c):

Input $\eta$: $\{NE, LI, NO, LA\}$ (9a)

Input $\tau_N$: $\{NE, LI, NO, LA, EX\}$ (9b)

Output $|\Delta s|$: $\{NE, LI, NO, LA\}$ (9c)

where the membership functions and their legends are given in Fig. 5. The algorithm output is determined using the linguistic rules in the following form:

IF $\eta$ is A and $\tau_N$ is B, THEN $|\Delta s|$ is $C$

where A, B and C are the fuzzy values of $\eta$, $\tau_N$ and $|\Delta s|$ respectively. For example, when the adjusting margin is large and active torque is normal, the adjustment derived should be normal. To avoid being over-sensitive, a dead-zone is assigned such that when the adjusting margin (or active joint torque) is "NE", no adjustment (NE) is made.

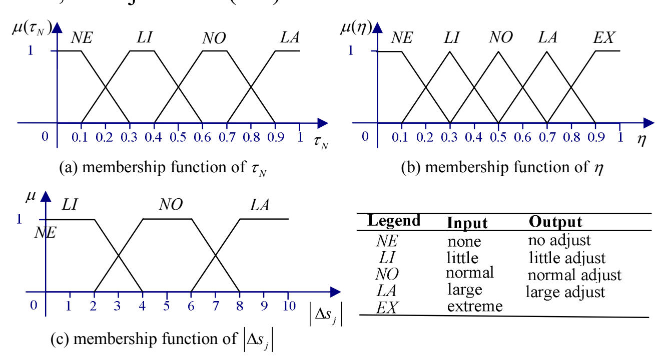



Fig. 5 Input and output membership functions

For a two-input system ($\eta$ and $\tau_N$ with four and five fuzzy values respectively), a fully populated rule base has 4×5=20 input rule combinations given in Table 2, where the braced decimal means the weight of that fuzzy rule in the Mamdani model [20]. The output membership function is defuzzified using the centroid method [20]. Since the deviation has the same direction as the active torque, the final adjustment can be calculated from (10):

$$\Delta s_j = \left|\Delta s_j\right| \mathrm{sgn}(\tau_{act}) \tag{10}$$

TABLE 2: FUZZY ADAPTATION LAW

| | | Adjusting Margin | | | | |
|---|---|---|---|---|---|---|
| | | **NE** | **LI** | **NO** | **LA** | **EX** |
| **Active Joint Torque** | **NE** | NC(1) | NC(1) | NC(1) | NC(1) | NC(1) |
| | **LI** | NC(1) | LI (0.2) | LI (0.5) | LI (0.1) | LI (0.1) |
| | **NO** | NC(1) | LI (0.5) | LI (0.9) | NO(1) | NO (0.8) |
| | **LA** | NC(1) | NO (0.8) | NO(1) | LA (0.8) | LA(1) |

The adaptation algorithm is executed using 4 iterative steps:

Step 1: Calculate the normalized active torque exerted by the patient from the inverse dynamic model and (8).

Step 2: Calculate the adjusting margin from (7).

Step 3: Given $\tau_{act}(j)$ and $\eta(j)$, determine the adjustment $\Delta s_j$ from the fuzzy adaptation law and (10).

Step 4: Update the trajectory, $\theta_r^{new}(j) = \theta_r(j) + \Delta s_j$ .

## B. Illustrative Application

The fuzzy adaptation algorithm has been written (in MATLAB) for simulating the effect of the fuzzy adaptation law on the reference trajectory to the patient-exoskeleton controlled system. As an illustration, a virtual patient with a periodic "abnormal right knee gait" is assumed. Numerical values used in the simulations are based on the LERE shown in Fig. 1 and Table 1. The upper and lower boundaries ($\hat{\theta}$ and $\underset{\smile}{\theta}$) of the normal gait are based on [14].

The algorithm follows the same steps outlined in the previous section except that the active torque of the virtual patient's knee is calculated using the following linear approximation:

$$\tau_{act} = k_p \left[\theta_p(j) - \theta_r(j)\right] \tag{11}$$

where $k_p$ is the impedance coefficient; $\theta_p$ and $\theta_r$ are the CP values representing the patient gait and the adaptive reference trajectory at the $j^{\text{th}}$ time instant. Without loss of generality, $k_p$ is assumed to have a value of unity. The trajectories (Fig. 3) are represented by Fourier series (1) where $K$=5 and $T_s$=0.08s for a gait cycle time of $T$=4s.

The adaptation process is best illustrated by the simulated results given in Figs. 6, 7 and 8 showing five iterations (denoted as Iterations 1 to 5) from the *initial* to the *final* adapted reference trajectory for one walking cycle. Figure 6 shows the effect of adaptive iterations on the knee/hip joint-coordination. The corresponding adjusting margin $\eta$ and the animated active torque $\tau_{act}$ of the virtual patient using (11) are graphed in Figs 7(a) and 7(b) respectively. Figure 8 compares the patient abnormal gait (denoted as "Patient Gait"), the initial reference (or a specified trajectory in-between the bounds of a normal gait [14]), and the final adapted reference trajectory. Some observations made are briefly summarized as follows:

– As illustrated in Fig. 8, an abnormal gait could significantly deviate from the normal gait boundaries. The adaptation algorithm takes three iterations to converse reducing the maximum active torque by 75% (Figs. 6 and 7).

– The local maximums $|\tau_{act}|$ occur at locations where $\eta$=0 (Fig. 6), the physical insights of which can be explained using Fig. 9 with (7) and Fig. 8:

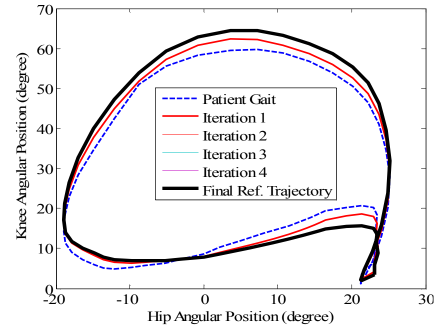


Fig. 6 Coordination between right knee and hip joints

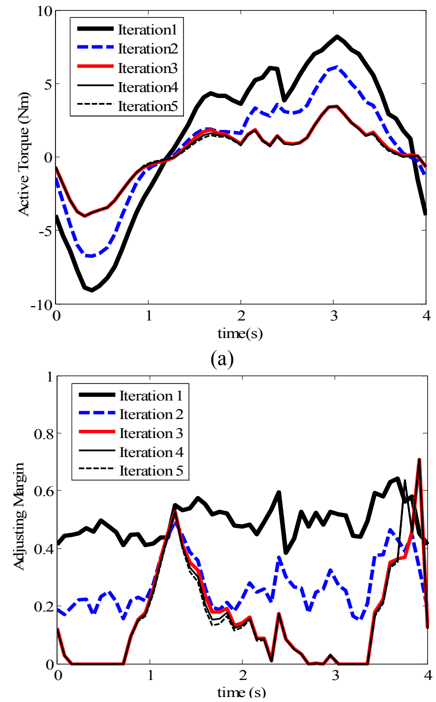


Fig. 7 Adaptation process of the algorithm

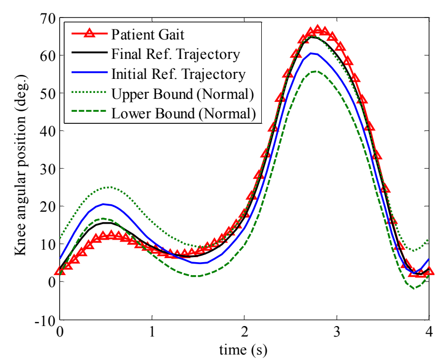
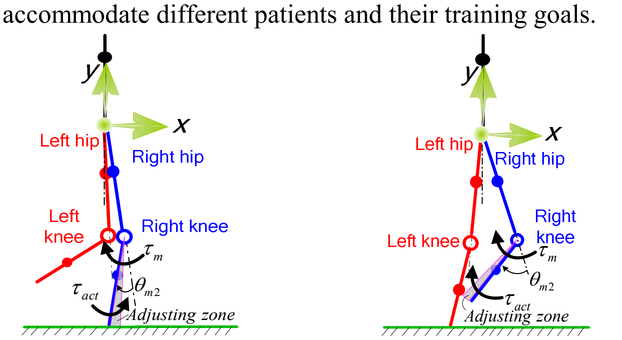


Fig. 8 Adaptation from initial to final reference trajectories

- Consider the interval $t$=[0, 1.2s] where $\theta_p$<$\theta_r$ and $\tau_{act}$<0. Figure 9(a) shows the posture when the right knee at its supporting phase and its corresponding $\tau_{act}$ has a local negative maximum. Since the reaction torque and friction are neglected, the right-knee motion is supported by the torques of the mechanical driver and the muscle contractions of the patient. Negative $\tau_{act}$ implies that the mechanical driver must supply an additional torque to overcome the opposing $\tau_{act}$. As defined by (7), the lower bound dictates when $\tau_{act}$<0. Provided that the reference $\theta_r$ is above the lower bound $\underset{\smile}{\theta}$, $\eta$ is set proportional to ( $\theta_r - \underset{\smile}{\theta}$ ) allowing for a trajectory correction to be made. The possible adjusting zone is shaded in Fig. 9(a), and has the same direction as $\tau_{act}$ according to (10); thus, the result is to decrease the angular displacement $\theta_{m2}$ and is consistent with the patient gait as shown in Fig. 8. When $\theta_r \leq \underset{\smile}{\theta}$, $\eta$ is zero (or NE in fuzzy linguistics) implying no adjustment (NC) and hence no further reduction in $|\tau_{act}|$.

- However, during $t$=[1.5s, 3.5s] where $\theta_p>\theta_r$ and $\tau_{act}>0$, the maximum $\tau_{act}$ is positive in the same direction as the mechanical driver, and occurs when the right knee in its swing phase as shown in Fig. 9(b). For $\tau_{act}>0$, the torque demand from the motor decreases, and the adjusting margin is dictated by the upper bound as defined in (7). As long as $\theta_r$ is below the upper bound $\overset{\frown}{\theta}$, $\eta$ is set proportional to ( $\overset{\frown}{\theta} - \theta_r$ ) to allow for correction on the reference trajectory. As shown in Fig. 8, the angular displacement of the mechanical knee joint can be increased approaching the patient original gait trajectory. Once $\theta_r \geq \overset{\frown}{\theta}$, $\eta$ is set to zero; no further adjustment on the reference (and hence $\tau_{act}$) is made keeping the patient gait near or at the upper bound.

– The above observations suggest that the adjusting margin η (along with the active torque $\tau_{act}$) offers an effective means to accommodate different patients and their training goals.




(a) Posture at negative max. $\tau_{act}$ (b) Posture at positive max. $\tau_{act}$

Fig. 9 Postures at the local maximums of $\tau_{act}$

## V. Conclusion

A model-based adaptation (MBA) mechanism for specifying an adaptive reference trajectory of a lower extremity rehabilitation exoskeleton (LERE) has been presented. The MBA mechanism consists of a trajectory generator, an inverse dynamic model that estimates the active torque of the patient, and a fuzzy adaptation algorithm. It offers an effective means to incorporate the experience of a rehabilitation doctor, accommodate walking patterns of different patients, and supervise during the gait training while minimizing the patient discomfort. Experiments with a passive healthy subject on the prototype LERE at Zhejiang University suggest that a complete inverse dynamic model can provide a useful alternative when active muscle contractions are not easily available. A fuzzy adaptation algorithm has been developed, and its effectiveness has been demonstrated numerically with an illustrative example.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