ITERATIVE LEARNING CONTROL METHODS IN WEARABLE ROBOTICS

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ABSTRACT

Robotics has become increasingly available to human life, due to technological advancement. One subset of robotics, which is emerging recently is wearable robotics. This field studies how robots can interact with humans physically and cognitively to overcome human physical limitations. For example, in clinical treatment, exoskeletons are used to assist patients with impaired muscle functions, sustain healthy muscle functionality and more. Safety and adaptability of the exoskeletons are the goals of the actuator and controller design. Here, several controller schemes are designed to provide comfort and flexibility to users. To improve the system's dynamic performance, Iterative Learning Control is presented. Iterative Learning Control(ILC) is a subset of controller methods. Its goal is to learn the system parameters to achieve the desired outcome, especially used in a nonlinear system where the system is prone to uncertainties and external noises. To improve system performance, ILC is integrated with conventional controllers, such as PID. In this literature review, three iterative learning control methods implemented in robotic exoskeletons are discussed and compared.

INTRODUCTION

Robotics has become increasingly important to human life. Not only that robots operate tedious and repetitive tasks in the industrial environment, separately from human operators, but they are also transitioning towards increasing interaction with the human actor. This human-robot interaction gives rise to a subfield of robotics called ‘Wearable Robotics’, where the robots, as the name suggested, are worn by human operators, whether to supplement a human limb or replace it completely. One important application of wearable robotics is used in clinical treatments, for example, to assist patients in restoring lost or weak muscle functions, and overcoming human physical limits.

According to research by Alami et al.(2006), discussing aspects of physical human-body interaction with robots, safety and dependability are the key factors in designing mechanism and control scheme. Considering these aspects, robots have to be stable and compliant with the human anatomy to provide comfort and flexibility. The proper dynamic behavior of wearable robots is achieved by the controller design. However, human-robot systems are often nonlinear, and difficult to model accurately. Thus, with the help of iterative learning controller methods, the controller performance is improved, reducing uncertainties and disturbances. This literature review will focus on three iterative learning control methods used in exoskeletons. The validity of controller performance is proved by given experimental data from the authors.

ADAPTIVE ITERATIVE LEARNING FOR UPPER EXOSKELETON ASSISTANCE

The iterative Learning Controller(ILC) scheme has been used frequently in recent research. The main characteristic of ILC is the ability to learn the nonlinear behaviors of a complex system efficiently, providing that the system involves in any repetitive task. Ruihua Wei *et al* implement ILC in their robotic exoskeleton, RUPERT IV, for repetitive upper-limb therapy. The team selected ILC to work in parallel with a conventional PID controller because only PID itself cannot guarantee consistent system performance due to the highly nonlinear nature of a coupled system of robot plus stroke’s human arms. The ILC incorporates the adaptive learning rate, in which its value is selected appropriately based on a set of fuzzy-based logic in order to capture the system's nonlinearity, not disturbances.

CONTROL SYSTEM DESIGN

The control system for RUPERT IV consists of two main components, the outer loop and the inner loop as shown in figure 1a[2]. The outer loop generates the desired trajectory planning, fed to the inner loop to control 5-DoFs joints individually. However, this research focuses on designing adaptive ILC in parallel with PID inside the inner loop to track the nonlinear error between the desired and current trajectories. The inner-loop control structure for RUPERT IV is shown in figure 2[2], where the error at iteration j is the input. Both PID and ILC are weighted to guarantee the initial-state conditions while capturing the system’s nonlinearity. Normally, ILC weights are around 60-70% for each joint. The

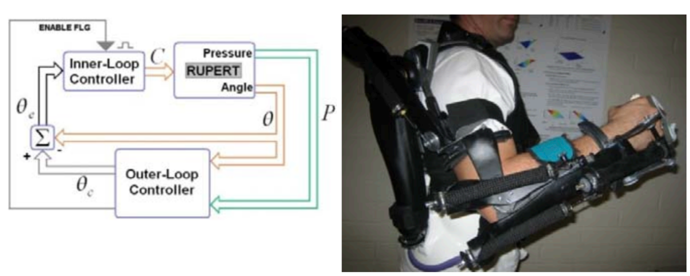

Fig. 1 (a) Overall Control Structure of RUPERT IV, (b) Structure of RUPERT IV [2]

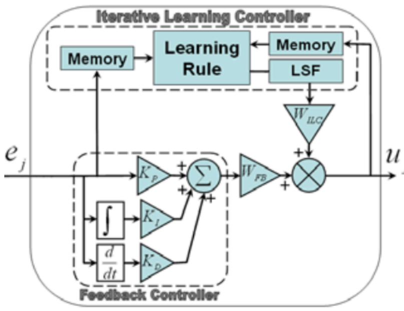

Fig. 2 Iterative Learning Control as a feedforward controller in parallel with PID inside the inner loop[2]

learning algorithm for this ILC can be categorized as causal ILC, where the error is taken from feedback inputs and desired and current trajectories of the same sampling time. The learning rate applied to the error signal is selected adaptively from the fuzzy-logic rule. There are 13 rules in total to adjust the learning rate which relies on 3 metrics including 1) Absolute Mean Error, 2) Standard deviation of the absolute mean error, and 3) correlation between the current error and the previous error. Based on these three matrices, the learning rate is chosen to track the underlying nonlinearity, not the disturbances. To ensure a smooth movement, the learned control signal is fit as a polynomial function of time. Finally, the iteration index is increased until convergence[2].

IMPLEMENTATION RESULTS

The control scheme is tested on 2 different male subjects. The goal is to test the adaptability of ILC+PID controller to 2 different subjects performing different tasks. Figure 3a[2] shows the actual joint position of the shoulder, elbow, and human rotation for iterations 1 and 7. The plots imply that the actual trajectory converges with the command trajectory, given a higher iteration. A different task is performed by subject 2 where he has to move each joint in a cyclical pattern for 4 iterations as illustrated in figure 3b[2]. This confirms that the controller has the consistent performance to track the command signal, robust enough to disturbances.

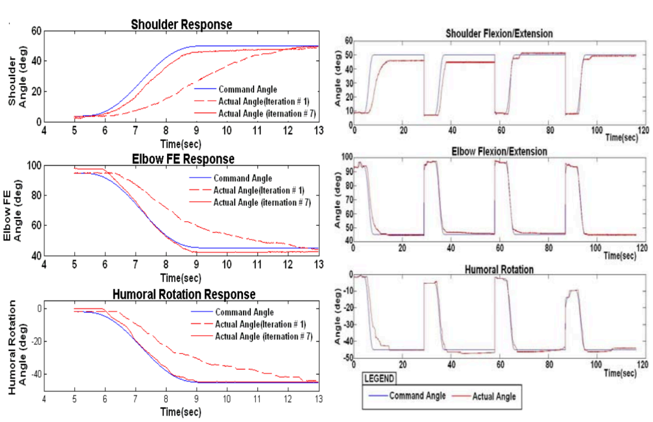

Fig. 3 (a) actual joint trajectories(red) for shoulder, elbow, and human rotation and command trajectories(blue). (b) cyclical patterns for different joint positions [2]

ITERATIVE LEARNING CONTROL FOR SOFT EXOSKELETON ASSISTANCE

Not only Iterative learning method is implemented in the upper limb exoskeleton but is also applied to the lower limb exoskeleton. In recent research presented by Chunjie Chen *et al,* the ILC is used to optimize soft exoskeleton assistance for hip and knee joints. The objective of ILC, in this case, is to decrease the tracking error, similar to RUPERT IV, but the method is different as the soft exoskeleton takes into account the wearing position and biological features to improve comfort and flexibility for different wearers. The challenge for a soft exoskeleton is that a direct dynamic model is difficult as it incorporates cables called, Bowen cables, to generate assistant forces which vary according to hip-joint angles. The system has to employ the angle information to predict the desired force trajectory depending on terrain variations(downhill, flat, uphill).

CONTROL SYSTEM DESIGN

The ILC in this research is called parameter optimal-iterative learning controller, or POILC in short. The task is to reduce any disturbance generated during walking on different terrains. In addition to POILC, Angles feed-forward directly measures the hip joint angle to compensate for the variation in the length of Bowden cables. Also, a PD controller is implemented as another layer for error tracking. All these three positional compensations are connected in parallel as in figure 4 [1].

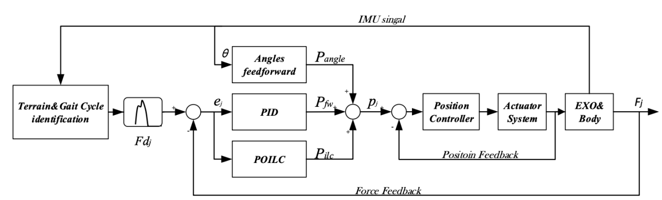

Fig. 4 Overall Control Structure for soft exoskeleton[1]

Unlike ILC in RUPERT IV, this is a P-type ILC, where the error is preemptively compensated. And the learning rate is computed so that the cost of each iteration is optimal. This ensures the convergence of ILC.

IMPLEMENTATION AND EXPERIMENTAL RESULTS

Experimentation is conducted in two main parts to evaluate the performance of POILC: 1) track the effectiveness of the robot assistance, and 2) present the performance in the form of the metabolic rate of the wearer. To test the performance of POILC, the overall force tracking is achieved from the relationship between hip angle and cable length. In the experiments, three healthy adult males are walking on a treadmill with variations in slope(+- 10 degrees and 0 degrees) to simulate different terrains. Figure 5[1] shows that POILC(purple line at 20th iteration) can track the desired tensional force(blue line) more accurately when the number of iterations increases. Although this is not as accurate as in

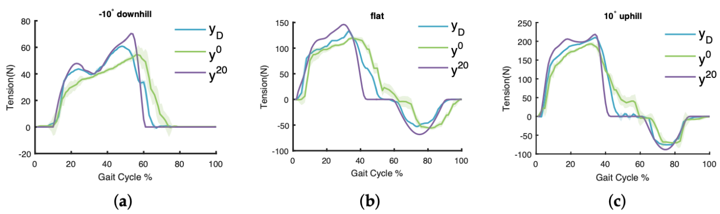

Fig. 5 Tension force tracking for different terrains (a) downhill, (b) flat, (c) uphill[1]

RUPERT IV, more concern is on response time and stability of the tracking system so that proper assistance is provided[1].

The performance evaluation is also tested in the form of metabolic cost. Different subjects participated to confirm the effectiveness. As shown in figure 6[1], a metabolic reduction is verified for different terrains by 9.86%, 12.48%, and 22.08% for downhill, flat, and uphill respectively. It is noticeable that the highest reduction in metabolic rate is for the uphill, in which the knee-joint moment is the highest[1].

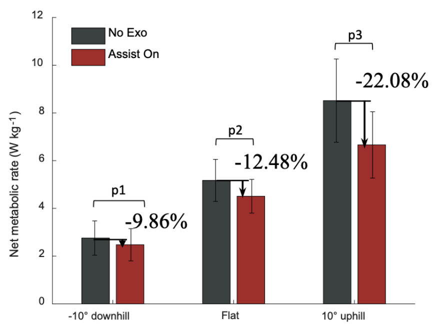

Fig. 6 Metabolic rate reduction of downhill, flat, and uphill[1]

ITERATIVE LEARNING OF ADAPTIVE GAIT PATTERN ADJUSTMENT

Another recent research on applying iterative learning control is done by Kyeong-Won Park *et al*[3]. The objective is to help people with complete paraplegia who cannot realize any movement of the lower limb walk in a natural gait movement. To achieve optimal assistance, ILC is appropriate for this problem because gait pattern varies for different users. Kyeong-Won Park *et al* tested the method on WalkON suit, a powered exoskeleton. Here to synchronize walking patterns with natural movement, ground contact timing is measured and the learning algorithm predicts based on that variable.

CONTROL SYSTEM DESIGN

As the walking gait pattern is individualized, the desired trajectory is generated to assist users optimally and is adjusted by ILC to learn the user's behavior in every iteration by taking into account hip and knee joints, and a trunk inclination angle, ϕ. The desired trajectory is fed to a disturbance observer(DOB) and a PID controller to reject any disturbances so as to improve tracking performance. Figure 7[3] illustrates the overall control structure for WalkOn Suit. Unlike the above two methods, the ILC is serially connected to the system.

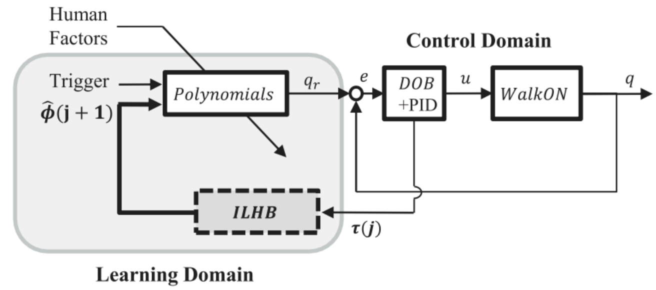

Fig. 7 Overall Control Structure for WalkON Suit[3]

To achieve the objective, ground contact timing is an essential factor that determines the ideal gait pattern for a user. The ideal contact occurs at 50%T of a gait cycle. In general, there is a misalignment between the ideal gait pattern and the actual gait pattern due to the complex dynamics of human-robot interaction. This issue causes early contact timing(<50%T) or late contact timing(>50%T), which can cause discomfort and injury, as in figure 8[3]. Thus, ILC's goal is to minimize erroneous contact timing.

The control algorithm calculates contact timing based on the transitional configurations of the stance and swing phases. This calculated timing is categorized into two cases: early contact(<0.5T) and late contact(>0.5T) according to human food intersecting with the ground. The ILC collects timing samples, calculates errors, and adjusts trunk inclination angles every iteration. The ILC learning rate is an inverse function of previous timing calculations. ILC gives the adjusted inclination angles for the next iteration. Finally, to decide the number of iterations, a performance objective is defined by an error norm of timing errors. The updated performance has to be lower than the previous ones[3].

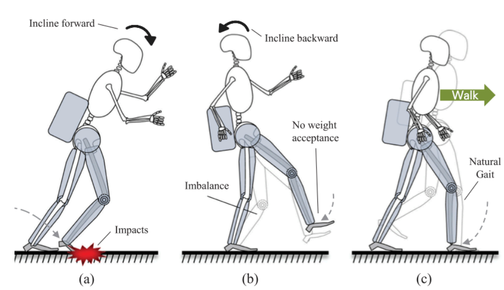

Fig. 8 (a) Early contact, (b) Late contact, (c) Ideal contact[3]

IMPLEMENTATION AND EXPERIMENTAL RESULTS

The experiment is conducted with two different complete paraplegia patients to ensure the stability of the system. For each subject, two initial conditions are set so that the first condition starts from early contact, while the second condition starts from late contact. As illustrated in figure 9, the early contact starts at setting 1(T(1): 45.53% < 50%), while the late contact starts at setting 2(T(1): 52.72% < 50%). Note that for both cases, the timing is converging to 50%T(ideal contact) for 20 iterations. This is true for subject B. The performance objective function decreases by more than 95% over the iterative period, in figure 10, verifying that the learning outcome is effective[3].

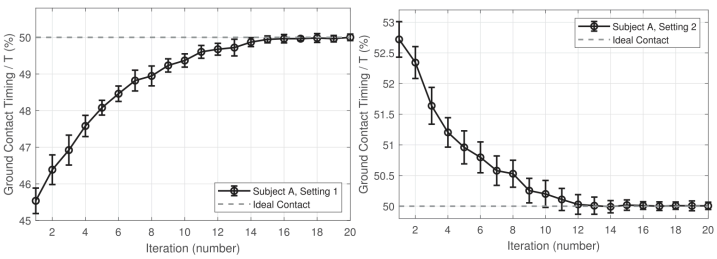

Fig. 9 (Left) Ground Contact Timing vs 20 iterations of subject A, setting 1 (Right) Ground Contact Timing vs 20 iterations of subject A, setting 2[3]

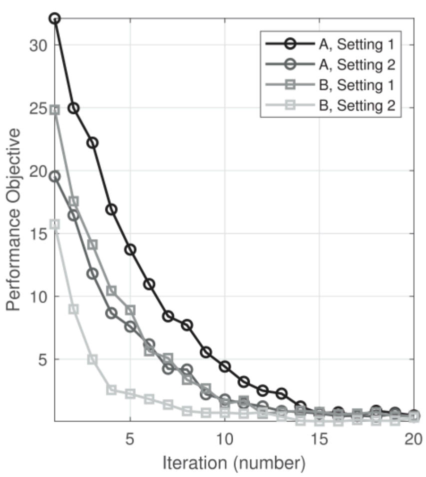

Fig. 10 Performance objective function over 20 iterations for subject A and B [3]

CONCLUSIONS

In this review, Three different Iterative Learning Controller methods(ILC) are applied to different actuator types in wearable robotics, both upper-limb and lower-limb exoskeletons. In complex repetitive-task systems, ILC has the potential to learn those systems effectively with less dependent on accurate dynamic modeling, which would be highly nonlinear. As Ruihua Wei *et al* presented in their paper that ILC is adaptive to track joints of 5-DoF RUPERT IV, given any disturbances. The learning algorithm is also able to select the learning rate based on error metrics, the higher the error, the higher the learning rate, and vice versa.

ILC is applied to soft exoskeletons as in the work by Ruihua *et al.* The task of ILC is different from RUPERT IV, which is employed in therapeutic exercises in that soft exoskeletons focus on assisting healthy users in less energy consumption, thus comfort and flexibility to the wearers are the main points. ILC is able to optimize the cable length based on the error between predicted and actual force assistance on different terrains(uphill, flat, and downhill), therefore increasing the comfort of users. However, the study of assistance strategy on a complex terrain is in future work.

Not only does ILC work on low-level control as in the case to reduce tracking error, but ILC is also able to work on the mid-level controller to generate a reference trajectory as illustrated in Adaptive Gait Pattern Adjustment. The control scheme can learn ground contact timing which is a function of biological data, in this case, hip joint, knee joint, and ankle joint to adjust the posture of the robot-human system as close to the natural gait pattern. This work is a huge step for paraplegic patients to walk independently with the help of wearable robots. For future work, different terrains are to be considered to develop the dynamic relationship between the desired motion and abnormal cases.

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