Tolerance of Neural Decoding Errors for Powered Artificial Legs: a Pilot Study*

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***Abstract*—Neural-machine interface (NMI) decoding errors challenge the clinical value of neural control of powered artificial legs, because these errors can dangerously disturb the user's walking balance, cause stumbles or falls, and thus threaten the user's confidence and safety in prosthesis use. Although extensive research efforts have been made to minimize the NMI decoding error rate, none of the current approaches can completely eliminate the errors in NMI. This study aimed at improving the robustness of prosthesis control system against neural decoding errors by introducing a fault-tolerant control (FTC) strategy. A novel reconfiguration mechanism, combined with our previously developed NMI decoding error detector, was designed and implemented into our prototypical powered knee prosthesis. The control system with FTC was preliminarily tested on two transfemoral amputees when they walked with the powered prosthesis on different walking terrains. Various NMI errors were simulated when the FTC was enabled and disabled. The preliminary testing results indicated that the FTC strategy was capable of effectively counteracting the disruptive effects of simulated decoding errors by reducing the mechanical work change around the prosthetic knee joint elicited by the NMI error. The outcomes of this study may provide a potential engineering solution to make the neural control of powered artificial legs safer to use.**

I. Introduction

Recent breakthroughs in powered artificial legs [1, 2] and neural-machine interfacing (NMI) technologies [3-7] have demonstrated great potential to improve the locomotion functions in lower limb amputees. The NMI has been designed to decode human's neural signals and interpret the user's intended locomotion tasks. The NMI, if connected with powered artificial legs, can potentially enable lower limb amputees to perform various locomotion tasks intuitively and seamlessly. Initial research have successfully integrated these two technologies for closed-loop prosthesis control, in which lower limb amputees were reported to be able to walk on varying terrains intuitively in a laboratory environment [5, 6].

However, none of the current commercial lower limb prostheses is neural controlled. One of the major challenges is the lack of robustness against neural decoding errors, which may trigger the erroneous action of prostheses, disturb the user's gait stability, or even cause loss of balance or falls. In order to resolve this challenge, almost all the current research effort focuses on minimizing the NMI decoding errors by exploring various machine learning algorithms [3, 8, 9], optimizing input data sources [10, 11] and features [12]. Recently, targeted muscle reinnervation technique has been conducted on lower limb amputees [5], in the hope of adding more neuromuscular control information contained in reinnervated muscles and further reducing the NMI errors. But unfortunately, none of the existing studies can eliminate the NMI decoding errors completely. Our previous research has systematically investigated the effects of commonly occurring NMI decoding errors [13, 14]. Errors that disrupted the prosthesis user's balance were identified (also noted as disruptive errors in this paper) and should be primarily addressed.

Instead of purely focusing on reducing errors in NMI, that is only one single component in prosthesis controller, we proposed to address the problem with an additional approach. Our new concept is to build an active fault-tolerant control (FTC) strategy within the prosthesis intrinsic controller (a controller that operate a prosthesis based on the mechanical feedback measured by the sensors within the prosthesis) to minimize, if not eliminate, the effects elicited by the disruptive NMI errors. The active FTC is generally composed of two key components: (1) an error detector that can promptly detect errors before the negative consequences happen, and (2) a reconfiguration mechanism that adjusts reconfigurable controller to compensate for the error-elicited impact [15]. Our previous study has indicated the importance of minimizing the mechanical work change at the prosthetic knee joint within around one hundred milliseconds after NMI errors occur in order to prevent the disruptive effects of NMI decoding errors [14]. In addition, NMI decoding errors can be detected around 80ms [16]. These studies imply it is very possible to reduce the disruptive effects of NMI errors if appropriate control reconfiguration can be applied to intrinsic prosthesis control parameters after detecting NMI errors.

The goal of this study was to design a FTC strategy, including a new reconfiguration mechanism applied to intrinsic prosthesis control and our previous error detector, to neutralize the disruptive consequences of neural decoding errors and improve the robustness of prosthesis controller. The FTC was implemented in our prototypical powered knee prosthesis and preliminarily tested on two transfemoral amputees. The outcomes of this study may lead to an effective solution to make the neural control of powered artificial legs safer and more practical to use.

II. Methods

A. Framework of a robust prosthesis controller with FTC

The FTC was integrated with our previously designed prosthesis controller, as shown in Figure 1. This controller consisted of two hierarchies: a NMI and an intrinsic

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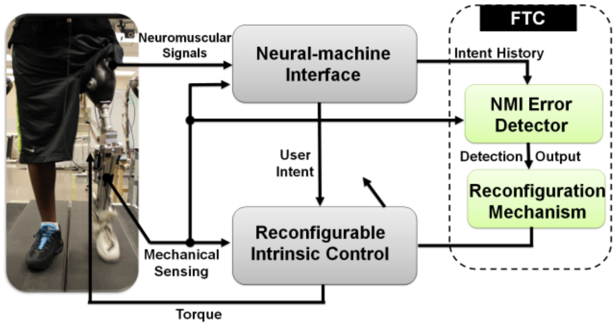

Figure 1. Framework of a robust lower limb prosthesis control system with fault-tolerant control (FTC).

controller. The NMI monitored the EMG signals measured from user's residual limb muscles and mechanical sensing information from the prosthetic itself, recognized user's intent, and then modulated the control mode in the intrinsic controller. In the intrinsic controller, a finite-state machine (FSM) and impedance control were applied to modulate the knee joint impedances based on the user's intended task (i.e. NMI output) and current state (i.e. gait phase). Different from our previous intrinsic controller [13, 16], in which the impedance parameters were pre-defined and fixed, current study applied a reconfigurable intrinsic control that can be modulated by the reconfiguration mechanism in FTC.

The FTC module is composed of two components: a NMI error detector and a reconfiguration mechanism. The NMI error detector monitors the NMI output and mechanical sensing information measured from prosthesis, and promptly detects NMI decoding errors to prevent the propagation of these errors on the prosthesis. Once an error is detected, the reconfiguration mechanism will be activated to adjust the control parameters in the reconfigurable intrinsic controller to reduce the error-elicited dynamic mechanical work change at the knee joint.

B. NMI Error Detector Design

Our previously designed NMI error detector [16] was applied in this study. A phase-dependent detector based on outlier detection algorithm was designed. Knee joint angular velocity and acceleration were used as the system inputs because these two combined measurements were found to be effective and responsive indicators of disruptive errors. The data when no error was introduced and correct task transitions were performed was used to build the normal condition model. The distance from a new observation to normal model was computed and compared to a threshold to make a detection decision. The threshold was determined to guarantee maximum detection sensitivity first while keeping false alarm rate as low as possible. To simplify the threshold optimization procedure, this study used the same detection threshold reported in our previous study. More detailed information about the detector design can be found in [16].

C. Reconfiguration Mechanism

Our previous study has indicated that the disruptive NMI errors were associated with large mechanical work change at the knee joint [13, 14]. Thus, our concept of reconfiguration mechanism was to minimize the mechanical work change elicited by the error after detecting a disruptive error. This was primarily achieved by reconfiguring the impedance applied to the knee joint to counteract the torque change triggered by the errors. An engineering trade-off was considered: (1) torque change elicited by the error must be minimized, and (2) additional disruptive effects caused by the false alarms in fault detector must be avoided. To do this, a weighted average approach was applied. Consider the case in which the NMI incorrectly identified the task *a* as the task *b*. When the fault detector detected this error, the applied knee impedance (I) was reconfigured as a linear combination of impedance for task a (I_a) and task b (I_b) according to:

$$I = C_a I_a + C_b I_b \qquad 0 \le C_a, C_b \le 1; C_a + C_b = 1 \qquad (1)$$

The two weight factors C_a and C_b at each time step were adjusted based the confidence of NMI error detector, which were calculated as Chi-square probability in outlier detection. The reconfigured impedance was applied until the end of simulated NMI decoding errors.

D. Experiment Participants and Measurements

Two subjects (TF01 and TF02) with unilateral transfemoral amputations were recruited in this study based on the approved Institutional Review Board (IRB) protocol at University of North Carolina at Chapel Hill. Informed consent forms were obtained from both subjects. Both TF01 and TF02 were male subjects and regular passive prostheses users in daily life. In the experiments, they wore customized suction sockets, which were attached to a powered knee prosthesis.

The robust prosthesis controller with FTC was implemented in LabVIEW environment and applied on a prototypical powered knee prosthesis developed in our group [17]. The powered prosthesis was controlled and tethered by the PC that ran the prosthesis control. The prosthesis was composed of a powered knee joint and a passive ankle joint. The knee joint was driven by a DC motor through a ball screw. More detailed information about design and control of this prosthesis can be found in [17].

The kinematics and kinetics of the powered prosthesis were measured by the intrinsic mechanical sensors instrumented on the prosthesis, including knee joint angle, angular velocity, and ground reaction forces and moments. The control modes and states (i.e. gait phases) of the prosthesis were also recorded. In addition, a wireless manual

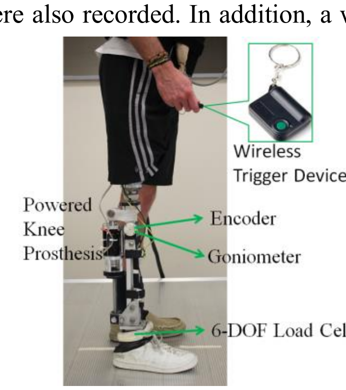

Figure 2. Experimental setup on one subject (TF02).

trigger device was used to record the subject's self-reported stability. All of these measurements were synchronized and sampled at 100 Hz. Experimental setup is shown in Figure 2.

E. Experimental Protocol

Prior to the experiments, both subjects already received 10-hour training to adapt to the testing powered prosthesis. This training was needed because the powered device was different from their passive devices used in daily life and the prosthesis control parameters need to be customized to each individual subject. After the training, both subjects wearing powered prosthesis were able to demonstrate stable and consistent gait patterns.

In the experiment, the previously identified disruptive NMI errors [14] were emulated. The error types included level-ground walking misclassified as ramp ascent/descent and vice versa. A NMI simulator was used to produce these disruptive errors when the subjects walked with the prosthesis on different walking terrains. In level-ground walking, the subject was asked to walk on a straight walkway; for ramp ascent/descent, the subject walked on a 10-foot ramp with 8-degree inclination angle. The same error was simulated twice, either with or without FTC being activated. Each testing condition (the error type and presence or absence of FTC) was randomly assigned in the testing trials. In addition, subjects were also asked to perform normal task transitions. Throughout the whole experiment, the subject was asked to report any gait disturbance event by pushing a button on the trigger device (shown in Figure 3). This signal was recorded to confirm the disruptive errors later. A fall-arrest harness system was attached to the subject to prevent falls. Rest periods were given between trials to avoid fatigue.

F. System Evaluation

To evaluate the overall performance of the designed robust prosthesis controller with FTC scheme, we quantified the subject's walking balance by examining their self-reported stability according to the recording from the trigger device. The number of errors that disturbed the subject's walking balance was counted and used as an evaluation metric.

In addition, to evaluate the effectiveness of FTC system to minimize the dynamic change caused by NMI errors, the amount mechanical work change (*ΔMW*) at the knee joint elicited by the errors was calculated. For example, for error that misidentified level walking (W) as ramp ascent (RA), the mechanical work change (ΔMW) is defined as:

$$\Delta MW = MW_{W(RA)} - MW_{W} = \int_{t1}^{t2} \tau(t)\dot{\theta}(t)dt - \overline{\int_{t1}^{t2} \tau_w(t)\dot{\theta}_w(t)dt} \quad (2)$$

where t1 and t2 are the timings when an error starts and ends, respectively; $\tau(t)$ is the torque applied to the knee joint; $\dot{\theta}(t)$ is the knee angular velocity; $\tau_W(t)$ is the knee torque in level walking; $\dot{\theta}_W(t)$ is the knee angular velocity in W.

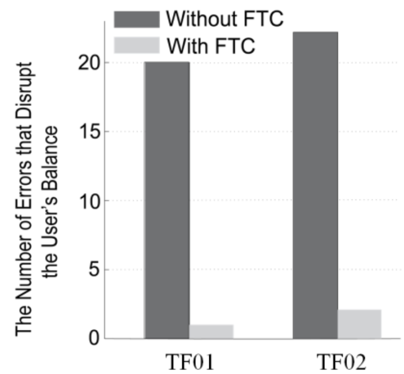

Figure 3. Number of disruptive errors observed in the experiments with and without using FTC.

III. Results

Figure 3 showed the number of errors that disturbed TF01 and TF02's walking balance when the FTC is activated and not activated. In total, 20 and 22 NMI errors were simulated on TF01 and TF02 during the testing session, respectively. When the FTC was deactivated, all of these errors were reported to disturb the subject's walking balance when they were simulated. In comparison, when the FTC was enabled, only one for TF01 or two errors for TF02 became disruptive when they walked with the testing powered prosthesis. Additionally, all the normal task transitions were performed smoothly by the subjects without any balance perturbations (i.e. no false alarm was generated from FTC system).

The mechanical work change elicited by the NMI errors with and without applying FTC was shown in Figure 4. When the FTC was disabled, all the disruptive errors caused large amount of mechanical work change at the knee joint (indicated by the red dots), which were out of the previously identified tolerable range (approximately between -0.04 and 0.04 J/kg) [13]. When the FTC was applied, the mechanical work change elicited by the errors was effectively reduced (linked by a line in Figure 4). Notably, for those errors that were recovered by FTC (non-disruptive errors), the elicited mechanical work change was reduced within tolerable range (indicated by the black dots).

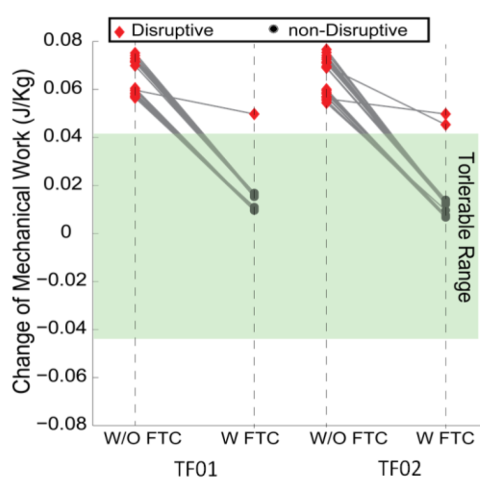

Figure 4. Change of mechanical work in initial double stance phase with and without using FTC.

IV. DISCUSSION

Neural decoding errors challenges the clinical value of neural control of powered artificial legs, because these errors, if directly connected with intrinsic prosthesis controller, may trigger the erroneous operation of prostheses, disrupt the user's walking balance, and thus threatens the user's safety and confidence in prosthesis use. Although extensive research has been done to minimize the NMI error rates, none of the current engineering solutions can offer error-free performance. Inspired by the FTC technique, which has been widely utilized in safety-critical system to minimize or eliminate the consequences caused by system failures, we presented an additional solution to resolve this challenge. The basic concept is to design an active FTC strategy to reduce, if not eliminate, the disruptive effects of NMI errors. In this study, the function of FTC was designed to minimize the mechanical work change by (1) reducing the duration of NMI decoding errors in action, and (2) counteracting the changes in torque caused by these errors. The preliminary results indicated that the applied active FTC strategy was capable of counteracting the effects of the disruptive errors by reducing the change of mechanical work around the prosthetic knee joint. The outcomes of this research is promising because it provides an additional engineering solution to significantly improve the robustness of neural controlled powered artificial legs and eventually make them practical for daily use.

Several limitations were still identified in this pilot study. First, the FTC was not tested in the closed-loop prosthesis control in current study. During the experimental sessions, the disruptive errors and task transitions were triggered by a NMI simulator. Therefore, evaluation of FTC on prosthesis with closed-loop control in action will be conducted in future study. Second, the types of locomotion tasks and considered errors were limited. Only most frequently occurring errors (i.e. errors between level-ground walking and ramp ascent/descent) were tested. Nevertheless, it should be noted that even though other types of errors (i.e. errors between level walking and stair climbing) rarely happened, once occurred, they may still disrupt user's walking balance [5]. Thus, our future study will test FTC on more terrain types.

V. CONCLUSION

In this study, we designed a FTC strategy to neutralize the disruptive consequences of neural decoding errors, aiming to improve the robustness of neuroprosthesis control. The FTC, including a novel reconfiguration mechanism and previously developed NMI error detector, was implemented into our prototypical powered knee prosthesis and tested on two transfemoral amputees. The testing results showed that the designed active FTC strategy can effectively counteract the error-elicited disruptive effects by reducing the mechanical work change around the knee joint caused by the errors. The outcomes of this study might provide an additional engineering solution to make the neural control of powered artificial legs safer and more practical to use.

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