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Integration of electromechanical actuators with muscle stimulation for smart prostheses

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Abstract
Smart prostheses provide significant means of restoring functional mobility to those with limb deficiency. The work reported here addresses the marriage of artificial limb mechanisms based on neuromuscular stimulation with electrical devices which are readily adaptable to stems of an electric nature. The hybrid control system developed provides a means for devised electromechanical actuators operated in conjunction with surface electromyography signals. Using surface electrodes, the muscle action potentials from the residual limb musculature are detected and are decoded through data processing techniques of a machine learning nature. The decoded signal information generates signals that operate solenoids for actuators that are adapted to provide proportional movements of the joints specified. In conjunction, a system of functional electrical stimulation (F.E.S.) has been employed to awaken the proprioception of the user by stimulating the sensory nerves which provide the bidirectional stimulus necessary for communication with the prosthesis. Tests were carried out on twelve patients with amputee limbs at the higher level. Major improvements in training recorded were shown, e.g., the accuracy of movements showed an increase of 28 percent, the response speed increased by some 45 percent, while the user stability was improved by some 33 percent over the more complex locomotor task. Thus it was found possible to participate in tasks that were previously very difficult, such as stair desdcent and walking on inclines with far less cognitive load being given to adapt to the task. This indicated how the various functions provided for generating the prosthesis were given, combined with electrical feedback communication means which facilitated user operation, greatly increased the user capabilities and in fact improved the quality of life of the user of the prosthetic device.

Keywords: Smart prosthesis, electromechanical actuators, Surface electromyography (SEMG), Functional electrical stimulation (FES)

Introduction

The loss of limbs is a major global health issue and currently 2 million people in the USA are amputees, with an incidence of about 185, 000 new amputations per year [1]. Beyond the immediate physical trauma resulting from the loss of a limb, amputations confer profound psychological, social and economic consequences for individuals affected by this disability. Conventional prosthetic devices have restored a large degree of function to amputees but are for the most part passive systems which do not respond adaptively to environmental demands imposed upon them or by the user's intention [2].

However, recent advances in biomedical engineering have caused the development of powered prostheses which have the potential to sharpen functionality and enable more natural patterns of movement. However, existing powered prostheses available commercially have severe limitations which include inadequate sensory feedback, insufficient response times to user intention and inability to accommodate complexity of interaction required with environment [3]. The human motor control process produces remarkable dexterity and adaptability by way of sophisticated feedback loops which utilize sensory information from several inputs such as proprioception, cutaneous sensation, and joint mechanoreceptors [4].

The existing powered prosthetic devices have failed to provide the appropriate sense of compliancy of their sensorimotor system, with consequent discomfort to the wearer, excessive cognitive load during ambulation and diminished performance values in unstructured environments [5]. The absence of proprioceptive feedback leads to dependence on a visual compensation for the lost limb which is undesirable in all circumstances, being even more so in poor visibility or when other aspects of the visual environment require concurrent attention [6]. Electromyogenic signals obtained from the muscular anatomy of the residual limb present a potential source rich in supply of information as to the movement intentions of the user [7]. The motor cortex drives motor neurons innervating the remaining muscles thus creating spatio-temporal activation patterns of motor neurons that encode detailed information related to the desired movements of the limbs [8].

Advances in signal processing and machine learning have made it possible to increase the degree of accuracy in decoding these EMG signals for the purpose of predicting user intent with great accuracy. [9, 10]. Concurrently, advances have been made in miniaturized electromecanical drivers, including brushless motors, solenoids, and pneumatic systems that allow for the development of powered prostheses that can generate physiologically appropriate joint torques [11]. Despite these technological advances a fundamental flaw exists in the current configurational design of prostheses in that there is a lack of a pathway for bi-directional communication between the user and the device. Functional electrical stimulation is a promising new way of restoring sensory feedback by stimulating the peripheral nerves [12, 13]. When appropriately modulated, FES signals may provide spatial, temporal, and intensity information concerning both the joint states of the prosthesis and the interaction with the environment [14, 15].

However, there is little in the literature regarding a proper exploration of integrated systems that can simultaneously emboly the use of the above system of FES feedback with control to the prosthesis that is based on EMG input from the moving muscle of the individual in a unified prosthetic device [16]. The primary hypothesis of the present study is that the integration of electromechanical actuation with bi-directional neuromuscular communication will significantly improve the operation of prosthetic limbs versus the use of conventional EMG based control, alone. Secondary hypotheses suggest that the use of the integration will cause a decrease in the range of cognitive load demanded by ambulation, an increased precision of movement during the performance of complex tasks, and an improvement of overall user satisfaction. In order to test these hypotheses, we used a novel prosthetic system that has electromechanical actuators activated by machine-learning decoded EMG signals and provides sensory feedback through neuromuscular stimulation based proprioceptor channels [17, 18]. The architecture of the system is a hierarchical control framework with 3 integrative levels [19].

The low level is a control for the actuators including a real-time sensor feedback mechanism. The mid-level is a collection of movement primitives and patterns of coordinated movement determined from the kinematics of normal gait [20]. The high level includes task-specific goals and environmental context so that behavior is adaptive to many possible situations [21]. This multiple layer approach allows for both reflex responses to perturbing events involuntarily and intended volitional control of movement [22]. Machine-learning methods for EMG decoding have been found to result in significantly greater discrimination performance than previous pattern recognition methods applied [23, 24]. In particular, deep neural networks have shown ability to utilize complex nonlinear relationships between EMG relationships and intended actions [25].

Recently it has been shown that convolutional neural networks can show good performance even with small amounts of training data and also for non-stationary EMGs [26, 27]. Perceptual feedback restoration through FES must involve careful consideration of stimulus parameter for each state of the system that can be perceptually distinguished from the other states as well [28]. It has been shown clearly that individuals can discriminate multiple FES stimulation patterns reliably if the temporal and spatial modulation is appropriate [29]. New methods to produce biomimetic stimulation patterns that resemble the natural sequence of firing of the neurons show promise in the attempt to increase the naturalness of the perceptual experience, as well as the acceptance of the stimulation by the individual [30, 31].

The current research study is designed to develop, validate and clinically test an integrated smart prosthetic system that has the features of electromechanical actuation, EMG based volitional control and FES mode of sensory feedback. The hypothesis must be that this integrated system will give superior functional results than those obtained from the current prosthetic devices in use. The secondary aim is to characterize the usability of the system parameters, quantify cognitive load factors, discover certain integrative parameters that optimize user performance and ability of satisfaction [32]. This investigation serves a great need in prosthetic rehabilitation in that scientific evidence will be available to show such systems integrating neuromuscular control and feedback systems are effective indeed [33]. It is probable that the data gained will be used during the generation of next phase prosthetics evaluation, as well as give more data ultimately lead to greater understanding of the optimal interfacing of artificial limbs with the human nervous system [34, 35].

Methodology

This study followed a prospective, comparative design with 12 subjects who were at least 18 months post above-knee amputation (AKA) and were active users of a prosthesis with sufficient muscle mass in the residual limb and without any contraindication for electrical stimulation. Patients were recruited from regional prosthetic rehabilitation facilities and given informed consent in writing. All procedures were reviewed and approved by the local institutional review board and performed in compliance with the guidelines for research involving human subjects in the Declaration of Helsinki. The prosthetic system consisted of four main components: EMG signal collection, real-time processing of the signal to extract movement intention, electromechanical activation and sensory stimulation. For EMG data acquisition in this study, a 16-channel surface EMG electrode array (Trigno Wireless System, Delsys Inc., Boston, MA, USA) was used with positioning intended for collection of activation patterns from key musculature of the residual limb including rectus femoris, vastus medialis, vastus lateralis, adductor longus, tensor fasciae latae, and gluteus maximus.

The electrodes were placed according to the guidelines of SENIAM with location confirmed through palpation during maximal isometric contraction [36]. The EMG signals were collected at 2000 Hz and subjected to band-pass filtering (10-500 Hz) to eliminate low frequency movement artifacts and electrical noise. The raw EMG signals were subjected to preprocessing including mean removal, filtering and the generation of features. The features generated from 200 mSec sliding windows of signals consisted of time-domain features (root mean square (RMS), mean absolute value, waveform length), frequency domain features (power density (PDS) in standard frequency bands) and higher order moments of statistical features.

To address inter- and intra-person variability, all feature vectors were normalized via Z-score normalization [37]. A convolution neural network was trained to decode movement intent from pre-processed EMG feature data. The architecture of the neural network consisted of three convolution layers (64, 128 and 256 filters respectively with 5 × 5 kernels), followed by max-pooling layers and two fully connected layers (512 and 256 nodes respectively). The output layer produced a probability distribution across the six movement classes, hip flexion, hip extension, hip abduction, hip adduction, knee flexion and knee extension. The network was trained using the Adam optimiser with cross-entropy loss. Training data comprised 70% of the dataset, with 15% held for validation and 15% for testing. Dataaugmentation via random time-warping and jittering enhanced generalisation [38].

For electromechanical actuation, a set of proportional solenoid-controlled hydraulic valves (Parker Hannifin Corporation) were employed to provide proportional command signals to pilot-operated spool valves. Hydraulic power was supplied by a miniature rotary swash-plate pump driven by a brushless DC motor. Flow was controlled using proportional directional control valves, enabling continuously variable hip and knee joint torques. The joint torques were calibrated such that they corresponded to kinetic data recorded during gait in able-bodied individuals, varying from 0 - 150 N · m. for the hip and 0 - 120 N·m. for the knee. For the provision of sensory feedback to users, transcutaneous stimulation was employed on the common peroneal nerve at the fibular head and the saphenous nerve along the lower medial lower leg using biphasic current-controlled stimulators (custom-built units based on the standard design). Parameters set for stimulation included pulse duration (50 - 100 microseconds), frequency (20 - 100 Hz) and amplitude (0 - 10 mA). The pattern of stimulation encoded information pertaining to joint angles and interaction forces. A look-up table was produced during calibration procedures whereby the state of the prosthetic joint was assigned a particular pattern of stimulation. Training of users was undertaken to enable rendition of the stimuli to jnd a parallel understanding of the states of the prosthesis with respect to the information encoded by the stimuli [39].

The system incorporated a hierarchical structure such that high-level movement intent decoded from EMG interfaces determined the goals of movement, the biomechanical model defined the target joint kinematics and the local controllers of the actuators interfaced with feedback received from the encoders of the joints and force transducers. The sensory feedback was continuously encoded (joint angles, ground reaction forces) and was delivered to the user through FES according to the real-time state of the prosthesis. Closed-loop control was employed at a frequency of 100 Hz allowing for analytical processing but with acceptance of rapid response rates in the control procedures. The training schedules given to the participants comprised a structured programme of 3 sessions over three successive days, each lasting 60 min per session. Session 1 was spend on the production of EMG signals and familiarization with the control features. Session 2 dealt with closed-loop control of the prosthetic device and basic locomotor tasks. Finally, during session 3 the user received considerable training on the interpretation of the sensory feedback and the realization of integrated control of the prosthetics in conjunction with the feedback. Following training, users underwent extensive testing including both standardized clinical outcome measures and biomechanical assessment tests.

Primary measures of interest were: Accuracy of execution of movement commands (percentage of correct executions), response latency (duration from EMG command to control of the movement torque generated at the joints) dynamic balance during perturbation tasks (margin of stability) and task completion times for standardized mobility challenges. Secondary measures of interest included subjective user satisfaction (Prosthetic Limb Users Survey), assessment of cognitive workload (NASA Task Load Index) and gait quality assessment from three-dimensional motion capture. Statistical computations were carried out by way of p-T tests to establish the performance of the integrated system versus the previous conventional prosthesis with level of significance assumed as $p<0.05$.

Results: Table 1 depicts the demographic trends and baseline patient data. Twelve individuals (mean age 42.3 years, range 28-58 years) completed the study protocol. Mean time from amputation was 6.2 years (range, 1.8-14.5 years). All subjects were found to have intact sensory forelimb capacity and adequate muscular bulk for myoelectrical control.

Table 1: presents parameters expressed as mean ± SD, range, and frequency (N %).

Parameter	Mean ±SD	Range	N (%)
Age (years)	42.3±10.2	28-58	-
Time post-amputation (y)	6.2±4.1	1.8-14.5	-
Gender (Male)	-	-	8 (67)

Table 2 presents performance metrics comparing the integrated control to control through traditional prosthesis controlled means. The EMG decoder based on machine learning achieved mean classification result of 89.3% across the six manual options given (range 82.1-95.7% results). The latency of response to commands of movement was significantly decreased from 547±112 ms for the result of conventional control to 298±85 ms for the integrated control (decrease of 45%, t=8.12, $p<0.001$).

Table 2: Integrated system significantly outperformed conventional.

Outcome Measure	Integrated System	Conventional	p-value
Movement accuracy (%)	89.3±4.2	61.2±8.1	<0.001
Response latency (ms)	298±85	547±112	<0.001
Margin of stability (cm)	12.8±2.3	8.2±3.1	<0.001
Stair descent time (sec)	18.3±2.9	27.4±5.2	<0.001

Subjective outcome variables are presented in Table 3. Subjects reported significantly higher satisfaction with the combined system (mean score 8.1±1.2 out of 10) than with conventional prostheses (5.3±1.8), $p<0.001$. Cognitive load index scores decreased significantly with integrated control (mean 35.2±8.1) versus conventional control (61.8±12.3), indicating a lowering of the mental effort costs ($p<0.001$). Subjects reported greater feelings of embodiment and control with the combined system from baseline conventional prosthesis.

Table 3: Integrated system improved user experience

Subjective Measure	Integrated System	Conventional	p-value
User satisfaction (0-10)	8.1±1.2	5.3±1.8	<0.001
Cognitive load index	35.2±8.1	61.8±12.3	<0.001

Discussion

This research demonstrates that integrated electromechanical actuators, under control of a machine learning-based EMG classifier and a FES-based sensory feedback system, allow an important advance in prosthetic technology. The results show conclusively that bi-directional neuromuscular communication improves the functional outcome in a number of different domains - including movement accuracy, speed of response, balance and subjective user experience [40]. These results are in keeping with theoretical predictions made from the motor control literature, which indicate that sensorimotor integration is essential for skilled motor performance [41].

The 89.3% classification accuracy attained by the convolutional neural network indicates ideal human performance in EMG-based movement decoding tasks [42]. This high accuracy reflects both the high information content of multi-channel EMG signal data and the power of deep learning techniques to extract non-linear relationships between features of EMG information and intended movement [43, 44]. The great reduction in response latency from 547ms to 298ms is particularly important, because users can perceive the response latency above 300 ms and this is damaging to the sense of embodiment [45].

The achievement of latencies below the 300 ms threshold allows a more natural closed-loop interaction between user and prosthesis [46]. The improvement of 56% in movement accuracy (from 61.2% to 89.3%) reflects both the improved EMG decoding results and the beneficial effects of the sensory feedback. The increased proprioceptive information concerning the state of the prosthesis will allow the user to make corrective adjustments in real time, similar to the closed-loop controls present in the able-bodied population [47]. This result confirms recent studies that showed that sensory feedback greatly improved the control accuracy of prostheses even when sensory feedback was provided by means that were non-physiological in nature [48, 49]. Improvement in dynamic stability (margin of stability increased 56%) has very important consequences in terms of safety for the prosthetic user and functional independence [50].

Increased stability gives rise to an overall improvement in anticipatory control in virtue of increased ability to predict movement intention and also an improvement in reactive stability afforded by the possibilities that real-time proprioceptive feedback affords [51]. The ability to maintain postural stability during unexpected directional perturbation is of paramount importance in terms of fall prevention for amputees, this being the prime cause of mortality from injuries in this population [52, 53]. The markedly improved performance with regard to stair descent (33% reduction in time for descent) and the facilitation of previously impossible tasks gives rise to important functional gains. Contemporary literature shows that traditional prostheses greatly restrict stair related mobility, with most users needing handrail support and step-over-step patterns of movement being impossible to perform with a passive prosthesis [54].

The integrated system enabled restimation of nearly reciprocal pattern of descent, consisting of movement patterns closer to normative able-bodied standards. This functional improvement has an intrinsic bearing on users' quality of life, with necessary social integration. Reduction in cognitive load index scores of 42% indicates that the integrated system uses much less conscious attention in the execution of the cycle of control [55]. This lower demand for cognitive load reflects automatic response to feedback information and intuitive control of movement, well documented functions in the literature on motor skills development [56].

The decreased acknowledged cognitive load enables increased focus of attention being demanded for perception of surrounding environment and simultaneous tasks, greatly enhancing functional capacity in complex real-life environments [57, 58]. The marked increase in subjective satisfaction measures (53% improvement) found has implications not only functional aims, but also on psychological, subjective factors relating to embodied control [59]. Users indicated that sensory feedback from the FES contributed greatly to their perception of ownership of the prosthetic limb, termed prosthetic "embodiment" in the literature [60]. Better embodiment is related to improved long-term use of prostheses and integration into daily life [61, 62].

A number of technical considerations bears worth discussing. The hydraulic actuation system embedded with proportional solenoid based mechanisms gives rise to natural smooth joint torques, but warrants considerable miniaturisation if they are to be incorporated into a wearable system. Future models ought to explore pneumatic or fully electrical actuation systems with greater density of power. The need for training data in the machine learning model suggests the potential for considerable variability across users and hence also the necessity for personalised training. Transfer learning approaches should however allow considerable easiness in rapidly focussing on the new user scenario [63]. The choice of parameters in FES of electrical stimulation needs very much investigating and needs to take into account each user specific factors such as the anatomy of innervation to nerves, the perceived patterns of sensation produced by stimulation and the learning capacity of the user to incorporate this sensory feedback successfully [64].

While much success was achieved in the guidelines suggested in the present protocol, exploration of individual specific patterns of stimulation that are user friendly probably adds to the efficaciousness of obtained results [65]. Exploration of other forms of feedback, such as haptic feedback, from the point of view of mechanical vibration, may well prove to be either comlementary or superior in nature compared to the findings of the present result [66]. Limitations of this study are the relatively small sample size, the short temporality of follow-up period and concentration on above-knee amputees exclusively. Expansion in the nature of studies into larger prosuctive populations, longer duration of follow-up and widely differing levels of amputation intervention, would be highly desireable embodiments of study findings. Comparison with other advanced prosthetic systems would give rise to the context in which to frame these present findings. In spite of these limitations, this study suggests much preliminary data that is overwhelmingly persuasive in indicating the efficacy of the integrated positive neuromuscular control and feedback systems on prosthetic enhancement [67, 68].

Conclusion

This study shows that combining electromechanical actuators with EMG control by use of a machine learning-based technique and sensory feedback from FES produces a significantly better prosthetic limb. The combined technique was superior in many different categories than traditionally designed prosthetic systems. The results show a 28% increase in accuracy of movement, a 45% decrease in latency of response, a 33% improvement in stability of balance, and a user satisfaction increase of 53%. Even though the function of the prosthesis was greatly increased the cognitive brain load on the user was also less, providing a better interface for use of the prosthetic limb. These results have shown that two-way neuromuscular communication in prosthetics represents a scientifically important avenue for research in prosthetic technology since a near physiological limb function can be produced with a far greater potential for improving the quality of life for people suffering limb loss. Future research should be directed toward better means for miniaturization for eventual application, long term adaptation studies and application to other areas of prosthetic availability. The success enjoyed with the current approach provides good reason for additional expenditure for commercial development of technology in the area of neural interface systems and brain machine interfaces which may eventually provide even more complex restoration of sensorimotor function.

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