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Using EMG for Real-time Prediction of Joint Angles to Control a Prosthetic Hand Equipped with a Sensory Feedback System

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Abstract

All commercially available upper limb prosthesis controllers only allow the hand to be commanded in an open and close fashion without any sensory feedback to the user. Here the evaluation of a multi-degree of freedom hand controlled using a real-time EMG pattern recognition algorithm and incorporating a sensory feedback system is reported. The hand prosthesis, called SmartHand, was controlled in real-time by using 16 myoelectric signals from the residual limb of a 25-year old male transradial amputee in a two day long evaluation session. Initial training of the EMG pattern recognition algorithm was performed with a dataglove fitted to the contralateral hand recording joint angle positions of the fingers and mapping joint angles of the fingers to the EMG data. In the following evaluation sessions, the myoelectric signals were classified using local approximation and lazy learning, producing finger joint angle outputs and consequently controlling the prosthetic hand. Sensory information recorded from force sensors in the artificial hand was relayed to actuators, integrated in the socket of the prosthesis, continuously delivering force sensory feedback stimulations to the stump of the amputee. The participant was able to perform several dextrous movements as well as functional grip tasks after only two hours of training and increased his controllability during the two day session. In the final evaluation session a mean classification accuracy of 86% was achieved.

Keywords: Myoelectric control, EMG signal acquisition, Prosthetic hand

1. Introduction

The control of upper limb prosthesis is an old problem. Current commercial devices use a two-site recording paradigm, enabling an open-close control scheme. Many different solutions to the control problem have been presented in the literature ranging from different placement of electrodes and different ways of interpreting the recorded EMG signals.

Sebelius et al. [1-3] used a virtual reality hand for training the amputees. Later, Pons et al. [4] used virtual hands for training amputees to control the MANUS hand prosthesis [5] using a three-bit sequential commands based on EMG. Cipriani et al. [6] used a four-command EMG-classifier and state machines to test different control strategies to command the Cyberhand [7] with 14 able-bodied participants. Using support vector machines (SVMs) and ten commercial Otto Bock electrodes, Bitzer et al. [8] were able to distinguish six classes of movements to control the DLR hand II [9]. Another method proposed by Nan et al. [10] used five EMG electrodes and a combination of Bayesian and neural networks to classify both location and motion in a cooking task, classifying six motions and six locations. Xinpu et al. [11] used a new method called smooth localised complex exponential (SLEX) to detect EMG features and a linear Discriminant analysis (LDA) to reduce the data set and a multi-layer perceptron (MLP) network to classify eight wrist motions using six electrodes placed on the forearm of healthy participants. Using four channels of EMG signals, Jun-Uk et al. [12] used a wavelet packet transform to extract a feature vector. This vector was subsequently dimensionally reduced using LDA, and a multilayer perceptron network was used to classify the outputs to nine hand motions. Ning et al. [13] used a signal processing algorithm for extracting proportional control information for multiple degree of freedom (DOF) control from EMG signals. A nonnegative matrix

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factorization (NMF) was used to estimate neural control information from the EMG signals. Tenore et al. [14] decoded individual finger movements (extension/flexion) of each finger (10 movements) using 19 electrodes for an amputee using traditional time-domain features and a multilayer perceptron as a classifier with an accuracy greater than 90%. Shenoy et al. [15] performed an online and an offline study using windowed RMS of the EMG signal as a feature vector and a support vector machine (SVM) as a classifier to control a 4-DOF robotic arm. Castellini et al. [16] used two conditions, still arm (SA) and free arm (FA), to evaluate three different grasps using seven electrodes and ten able-bodied participants using SVMs. User-selected intentional movements were decoded in real time using EMG collected from two sites by Momen et al. [17]. Features were extracted using the natural logarithm of RMS values, and the feature space was segmented using a fuzzy C-means clustering algorithm. For a review on myoelectric control systems, see Oskoei et al. [18].

A procedure that requires a more invasive approach, named targeted muscle reinnvervation (TMR), was suggested by Kuiken et al. [19], where nerves that used to innervate the arm are transferred to the chest muscle. None of these earlier works on myoelectric control have used multidimensional continuous sensory feedback to the user. Here, the first evaluation of a multi-degree-of-freedom prosthetic hand for transradial amputees controlled using a real-time EMG pattern recognition algorithm and incorporating a sensory feedback system is reported. The hand prosthesis was controlled in real time by using 16 myoelectric signals from the residual limb of a 25-year old male transradial amputee in a two-day-long evaluation session. We have previously reported on a similar experiment [20] using another type of prosthetic hand and a different EMG recording setup.

2. Materials and methods

2.1 The SmartHand prosthesis

The SmartHand underactuated prosthesis [21-24] was used in the experiment (cf. Fig. 1). Sixteen DOFs (three for each finger, plus one for the thumb opposition axis) are operated using nylon coated steel tendons, pulleys and steel Bowden cables by four non-back-drivable actuation units based on DC motors located inside the palm. The thumb and index finger are independently actuated, whereas the middle, the ring, and the little fingers are jointly actuated. This is implemented using a differential mechanism placed inside the palm. Another motor is used for the thumb ab/adduction axis movement, in order to allow different grasping patterns useful in everyday life. The presented actuation distribution allows the hand both to perform fundamental grips useful in activities of daily living (power, lateral and precision grips) and to perform the important task of independently pointing the index (useful for typing, press buttons, etc.). Novel non-back-drivable actuation units were also designed to reduce power consumption [22].

Figure 1. SmartHand prosthesis (left) and myoelectric hook (right) normally used by amputee.

In order to implement automatic control loops within the hand, and to deliver sensory feedback to the user, the hand is equipped with 32 proprioceptive and exteroceptive sensors: 15 Hall effect-based joint sensors (integrated in all the finger joints), five strain gauge-based cable tension sensors (as in [7]) integrated in the fingertips (thus measuring the grasping force of each finger), four current sensors (one for each motor) and four optical-based tactile/pressure sensors in the intermediate and proximal phalanxes of the thumb and index. Actuation units are also equipped with position sensors (measuring the released tendon length) and a pair of digital limit switches (to avoid mechanical collisions) [23].

In a prosthesis advanced both in terms of number of active DOFs and comprehensive sensorial system such as this one, the electronic architecture has to be flexible enough to support the real-time control of four active axes, real-time identification of external commands, computation of control loops and delivery of sensory feedback. To this aim, a modular hierarchical design [7] based on an high-level hand controller (HLHC) and two low-level motor controllers (LLMCs) has been selected. Both LLMCs are associated with two actuators, while the host HLHC is in charge of the general functionality of the prosthesis. The HLHC, in master configuration, communicates through a fast SPI bus with the slave LLMCs, whereas the User-Prosthesis Interface (or a PC for diagnosis) may deal with the HLHC using a standard RS232 communication bus.

2.2 EMG acquisition system

The custom-built 16-channel EMG acquisition system (see Fig. 2) consists of two sandwiched PCB's, one containing the electronics for amplification and filtering of the EMG signals and one for sampling and communicating the signal onwards. The PCB's outer dimension is 70 mm × 130 mm. A quad operational amplifier (OPA4344, Texas Instruments) is used to amplify and band-pass filter the EMG signal for each channel. Each amplifier has a 55 dB gain and –3 dB points at 100 mHz and 1 kHz. The amplified and filtered EMG signals are

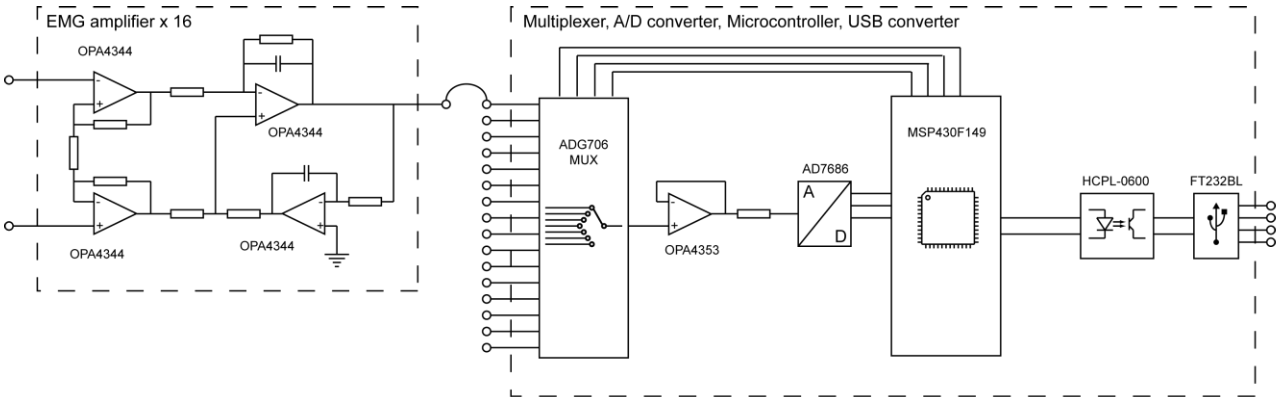

Figure 2. Block diagram of the 16-channel EMG-acquisition system.

connected to the inputs of a multiplexer (ADG706, Analog Devices). A microcontroller (MSP430F149, Texas Instruments) selects, in turn, one of the EMG-inputs, and this signal is connected to a voltage follower (OPA4353, Texas Instruments) with a high slew rate (20 V/μs) and then passed on to a 16-bit A/D converter (AD7686, Analog Devices). An SPI communication link between the microcontroller and the A/D converter handles the setup of the A/D-converter and sampling of the data. The sampling rate of the A/D converter is 2 kHz per EMG-channel. The microcontroller sends the collected EMG-data in bursts with all 16 channels in one burst at a speed of 2 Mbit/s through a USB serial port. An opto-coupler (HCPL-0600, Fairchild Semiconductor) is used to galvanically isolate the EMG system (directly connected to the patient) from the USB-serial interface (FT232BL, FTDI Chip). The serial interface uses RS-232 communication over USB and can consequently be connected to a PC.

2.3 The tactile display

The tactile display consists of five servomotors as actuators (Graupner DS281, Graupner GmbH, Germany), controlled by pulse width modulated (PWM) signals generated by a stand-alone electronic control system employing a microcontroller (MSP430F149, Texas Instruments). Buttons (12 mm in diameter) at the end of the actuators exert pressure on the skin, activating mechanoreceptors, hence giving rise to a tactile sensation. The use of five actuators corresponds to feeling the pressure of each fingertip of the hand. Each actuator can exert ten discrete levels of skin displacement, comparable to ten discrete levels of pressure. The tactile display was placed on the stump of the amputee in a pattern corresponding to the fingertips of the hand that is sensorically replaced. It is held in place in the prosthetic socket with an elastic bandage. The tactile display is connected to the sensors on the prosthetic hand in such a way that a stimulation of one of the prosthetic fingers gives rise to a similar, but displaced, stimulation on the skin of the amputee. This system is equipped with a standard RS232 serial interface for receiving control commands from a computer or prosthesis system.

2.4 Software and training setup

A data glove (Cyberglove, Virtual Technologies, USA) was fitted on the healthy hand of the amputee. Sixteen Ag/AgCl electrodes (3M) were placed on the stump of the amputee. These electrodes was subsequently connected to the previously described EMG acquisition system, and the EMG acquisition system was connected to a computer. The amputee was then asked to perform the same movement with both hands, mapping EMG signal activity to data glove movements. The data glove records joint positions of the fingers using 18 finger-joint angle sensors. A custom-made application (in Visual C++) using local approximation and lazy learning was responsible for the mapping of the EMG signals to data glove movements, i.e. filtered EMG patterns were stored along with the corresponding finger positions. The eight output positions best fitted to the unknown EMG pattern were searched using a full search of the stored dataset, and the associated output positions were then mean-averaged, forming the predicted movement [2]. In this way, the system learns to map muscle activity to hand movements. After the initial learning phase, the algorithm can predict movements based on EMG activity and thus control the prosthesis.

The EMG signals were filtered to remove the baseline, rectified and then filtered with a filter similar to a moving average filter [2]. Similar methods have also been used in [14] and [15]. The EMG signals were read in blocks with a period of 50 ms, which was fast enough for the control to be considered as smooth and real-time. The mean value of the filtered EMG, for each 50 ms block and from each channel, was then used as a feature for the pattern recognition algorithm. A time window of the five latest blocks was used for the prediction, thus covering EMG data 250 ms back in time. Thus, the input space for the pattern recognition algorithm was 16 channels * 5 data blocks = 80 inputs. The output space of the pattern recognition algorithm was the 18 finger joint angles. These joint angles were further processed to fit the control commands for the four motors of the SmartHand prosthesis. These algorithms and methods were investigated in an earlier work and found to be high-performing. In this work, they were used together with a real prosthetic hand on an amputee.

The pattern recognition algorithm was trained using data only from the training sessions, and then the system was validated with data only from the validation sessions, (see section *2.6*, *Myoelectric control experiment*). The criterion for a correct performed movement was if the amputee was able to complete the specific movement within three seconds. To

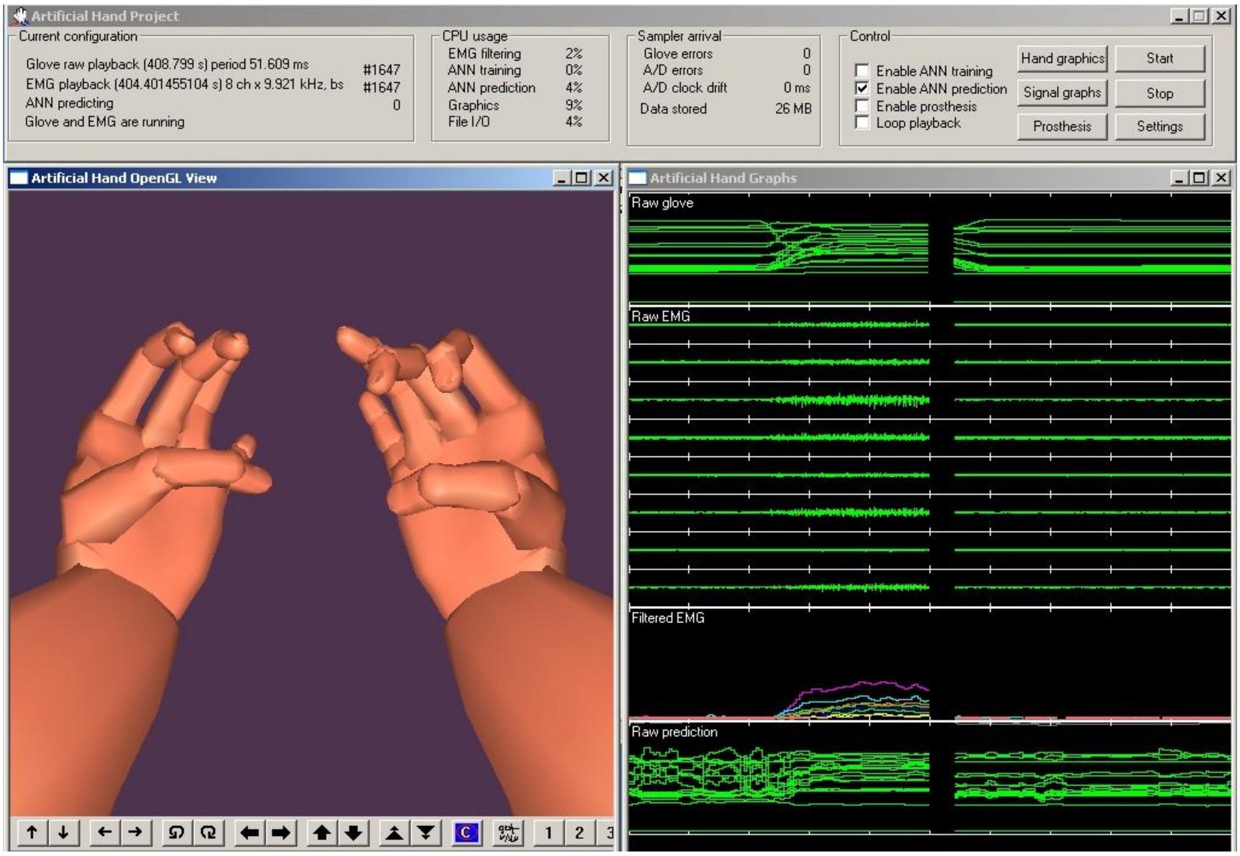

Figure 3. SmartHand control and training program.

mathematically compute if the intended movement was reached, the reference positions was compared with the predicted angles and the Euclidian distance was used for finding whether the end point was reached.

In order to keep the system flexible, it was built to run on Microsoft Windows. In addition to performing the training and control operations, the program also contained a user interface giving the operator detailed control over almost every aspect of the signal path. It was also possible to view all signals graphically and store them for off-line analysis (cf. Fig. 3). With this system, it was possible to investigate initial localization of electrodes and to optimize parameters, facilitating the training of the amputees. With this setup, amputees should be able to train and increase controllability performances in real-time. The Visual C++ application previously described was used to communicate with the SmartHand, the EMG acquisition system and with the tactile display.

2.5 Socket and integration

The components previously described have been integrated and interconnected with a prosthetic socket to form a bi-directional interface, fitted to a 25-year old transradial amputee. An Icecross Upper-X liner (Össur, Iceland) was put on the stump of the amputee and an Icelock 700 (Össur, Iceland) was used to secure the liner to the socket. An Otto Bock quickdisconnect wrist connector was used at the wrist level to connect the socket to the SmartHand prosthesis.

Holes were cut out of the socket and liner to enable placing of electrodes (Ag/AgCl, 3M) and the actuators for the tactile display on the forearm skin. Sixteen electrodes for the EMG acquisition and five actuators for the tactile display were used in the experiment. The electrodes were placed on the superficial flexor muscles on the volar side of the forearm and on the superficial extensor muscles on the dorsal side of the forearm The SmartHand prosthesis mounted onto the socket and on the amputee is shown in Fig. 4.

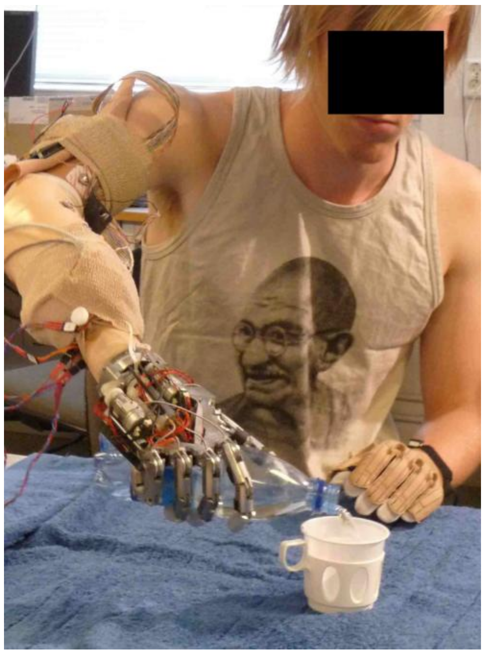

Figure 4. Amputee with the SmartHand prosthesis system.

2.6 Myoelectric control experiment

A preliminary evaluation of the SmartHand system was conducted on a 25-year old transradial amputee. He had lost his hand due to cancer in the wrist three years prior to the tests. The participant was instructed to perform seven movements: A: thumb flexion, B: index finger flexion, C: thumb opposition, D: middle-little-ring finger flexion, E: tridigital grasp, F: lateral grip and G: cylindrical grasp. All movements were performed synchronously with the contralateral healthy hand, and as the positions from this hand were recorded using the dataglove, it was possible to train the system on continuous movements, but also to validate the performance of the continuous predictions of movements.

The experiment was divided into two types of sessions, i.e. a training session and an evaluation session. In the training session, the pattern recognition algorithm was used to map EMG signals picked up from the amputee's stump to hand movements performed synchronously with the dataglove worn on his intact hand. Hence, EMG signals were associated to glove movements in the pattern recognition algorithm. In the evaluation session, the pattern recognition algorithm was used to predict hand movements based on EMG signals and thus to control the prosthetic hand. In each of the sessions, three repetitions of the seven movements were performed. After each evaluation session, the pattern recognition algorithm was cleared of its training data and a new training session followed. The experiment was performed over two days, and the two last evaluation sessions for each day were used for the statistics reported here. One trial was done at the beginning of each day so that the participant could "learn" the movement. After that followed five sessions to train the participant and finally the two evaluation sessions. The amputee was also allowed to test the prosthesis freely between sessions four and five.

Initially, the participant was trained to make the movements without interaction with objects and with the prosthetic hand and his arm resting on the table. In the end of this preliminary evaluation, some functional tests such as picking up and placing different objects or pouring water from a bottle were performed.

3. Results

The participant was able to control up to five different movements, including individual finger movements, with a high accuracy during the two-day experiments. In the end, he could also perform functional tasks such as picking up and placing objects and pouring water from a bottle into a glass (see Fig. 4). In Table 1, the accuracy of moving the fingers to a specific posture or movement is shown. The movements that were easiest for the participant to perform were thumb flexion, thumb opposition and flexion of all fingers, which were correctly classified (100% accuracy) in all evaluations. The movements that were hardest for the participant to perform were the grips; i.e. pinch grip and lateral grip, gaining a maximal classification accuracy of 67% and 33% respectively.

In Fig. 5, continuous prediction of joint angles, which was used to control the SmartHand prosthesis, is shown. From top to bottom, the angle for little finger flexion (LF), ring finger flexion (RF), middle finger flexion (MF), index finger flexion (IF), thumb flexion (TF) and thumb opposition (TO) are shown. The signals are represented in full scale, i.e. any maximum value in the diagram represent a fully closed finger, while the minimum value represent a fully opened finger. The X-axis represent the time in seconds. The seven movements, in Fig. 5, noted A-G, are all from the last session of the second day of the experiment. Movement descriptions can be seen in Table 1. The dashed lines are recorded hand position of the opposite hand that was fitted with a data glove. The participant was instructed to do synchronised movements with the existing hand and the phantom (non-existing) hand, and therefore, the recorded data from the existing hand equipped with the dataglove could be used as the desired joint angles. All performance data was calculated by using "unknown" recorded joint positions, i.e. training and validation datasets were separated. The last two types of movement, pinch and key grip, were least alike the continuous reference signal, which corresponds well with the overall analysis presented in Table 1.

Table 1. Results from the two-day myoelectric control experiments.

Movement	Day 1		Day 2	
	Eval. 1 [%]	Eval. 2 [%]	Eval. 3 [%]	Eval. 4 [%]
A: Thumb flexion	100	100	100	100
B: Flexion of index finger	67	67	100	100
C: Thumb opposition	100	100	100	100
D: Flexion of little, ring and middle finger	100	100	67	100
E: Flexion of all finger except the thumb	100	100	100	100
F: Pinch grip	33	33	33	67
G: Key grip	0	0	33	33
Mean	71	71	76	86

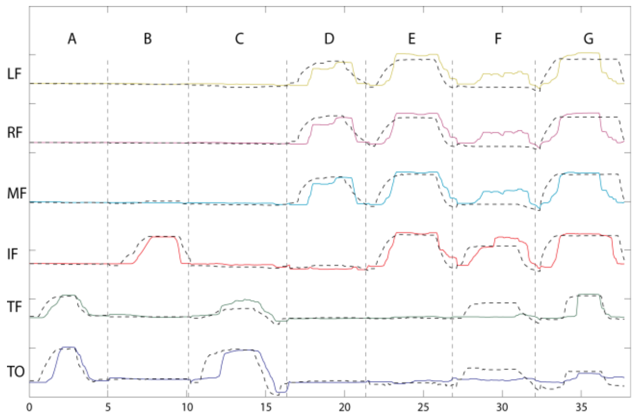

Figure 5. Continuous prediction of joint angles, little finger flexion, ring finger flexion, middle finger flexion, index finger flexion, thumb flexion and thumb opposition, top to bottom, versus recorded angles from the contralateral hand using a data glove. The desired values (data glove) are represented by dotted lines. A-G represents the different movements (see Table 1).

4. Discussion and conclusion

An amputee was fitted with a custom-built moulded socket containing an EMG recording unit, a sensory feedback system with actuators pushing on the skin of the forearm stump, a processing unit and a multi-DOF, dexterous, sensor-equipped prosthetic hand. The prosthesis was controlled with the residual muscles in the forearm using a 16-channel EMG amplifier and a pattern recognition algorithm, and the artificial sensory information from the five fingers of the SmartHand was relayed to the forearm using five actuators. The amputee was able to control five different finger movements correctly and could also perform functional picking up and placing tasks.

Looking at the continuous predicted joint angles and recorded signals from the data glove in Fig. 5, the thumb opposition is activated almost to the same extent as in the movement with thumb flexion. This is probably caused by limitations of the functionality of the data glove, i.e. flexing the thumb generates a stretch in the fabric of the glove which stretches the thumb opposition sensor. However, the thumb flexion sensor was not activated for the thumb opposition movement, and in the end, there was still a distinct difference between these two movements.

The amputee was using the sensory feedback system during all tests, which could have had impact on how well the amputee controlled the prosthesis. The sensory feedback system could also affect rehabilitation and increase learning of the myoelectric user, as sensation is essential for the learning of motor function. However, this was not investigated and would be of interest for future work.

In this study, 16 EMG channels were used, which must be considered high compared to earlier reported works. The high number of electrodes could probably be reduced without a significant drop in performance, as reported in [25-27]. However, it seems likely that electrode localization would be more crucial for a setup with fewer electrodes and would also depend on the length of the remaining forearm.

The amputee was at the end interviewed, and he expressed that initially using the SmartHand prosthesis he felt strange as he had not used his hand in several years and suddenly being able to move and feel with his “hand” was for him an amazing feeling. Some of the future work could be to assess if sensory feedback could increase body belonging experience, which is believed to be an important factor for the acceptance of a prosthesis by amputees.

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