Methodologies for determining minimal grasping requirements and sensor locations for sEMG-based assistive hand orthosis for SCI patients

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Abstract— In this paper, we address two of the most important challenges in development and control of assistive hand orthosis. First, supported by experimental results, we present a method to determine an optimal set of grasping poses, essential for grasping daily objects. Second, we present a method for determining the minimal number of surface EMG sensors and their locations to carry out EMG-based intention recognition and to control the assistive device by differentiating between the hand poses.

I. INTRODUCTION

Approximately 45% of SCI patients have difficulties in fulfillment of activities of daily living (ADL) owing to insufficient hand function, despite having residual function in arms and shoulders [1]. Assistive hand devices have been developed to help SCI patients with their daily activities [2]. Active assistive devices have the advantage of enhancing patients' grasping or opening force and acting based on user's intention [3], [4], [1].

Intention recognition methods based on Electromyography (EMG) signals, extracted from user's muscles are commonly used methods in controlling active orthoses due to several advantages. Firstly, employing task related muscles makes the operation of the device more intuitive and reduces the training time. Secondly, operation of the assistive device is not disturbed by the movements of other body parts. Several user interfaces of current active assistive devices sense the movements of other body parts such as tongue [5], neck [6], wrist [7], or receive voice commands to recognize user's intention [8]. In order to successfully use these interfaces and operate the assistive device, the user has to stop speech or head or wrist movements. In addidtion, using the movements of other body parts may restrict the scope of available tasks. For instance, using a hand orthosis that is operated by the wrist motion, a user may not be able to accomplish a task that needs simultaneous movement of hand and wrist (e.g, opening a jar).

A few researchers have developed EMG-driven active hand orthoses for patients with neuromuscular disorders and spinal cord injury. Thus far, the operation of these devices has been performed only with one variable. Benjuya and Kenny [3] were the first team to develop an EMG-driven

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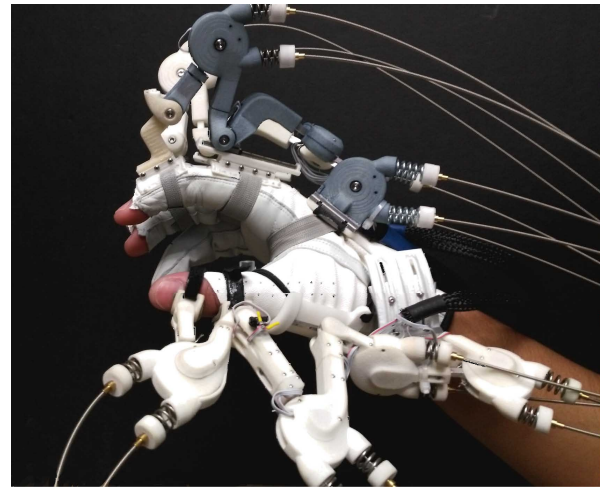
Fig. 1. Maestro has three actuated fingers and 8 DoF. It can provide various hand poses that are required in ADL as an assistive orthosis.

1-DoF assistive finger exoskeleton. Their device had been tested on one subject with brachial plexus and two C6 level SCI subjects according to American Spinal Injury Association (ASIA) impairment scale. The article reports the enthusiasm of patients while using the orthosis. Dicicco et al. [4] developed a 1-DoF orthosis for assisting pinching motion of SCI patients. The paper reported that while using the orthosis a C5/C7 SCI subject was able to grasp a roll of tape, rubber ball, hockey puck and he was unable to grasp a tooth brush and a deck of cards. Zhao et al. [9] recently presented a soft hand orthosis which is capable of increasing grasping force proportional to a one-dimensional EMG-related variable. The paper demonstrates potential of soft actuators in hand orthoses but does not show experimental results with patients with neurological disorders. Since, all the previous works have controlled a device with only a one-dimensional variable, EMG signals have been used, in a one-dimensional threshold control or proportional control. However, in this way, the user is able to grasp only a limited number of objects.

Many grasping poses are used by humans in daily activities. Bullock et al. [10] reported that humans use 34 different hand poses for grasping objects, and Sollerman [11] selected the eight most frequent hand grips for grasping objects required in ADL. In order to grasp daily objects with various shapes and properties, a hand orthosis needs to generate various hand poses depending on the object.

On the other hand, differentiating between numerous hand

poses besides recognizing the user intent, especially with noisy nature of EMG signals is also a great challenge. Moreover, surface EMG (sEMG) sensors are not able to accurately monitor activities of individual muscles. Consequently, similar muscle activity patterns are measured while grasping different objects requiring fairly different hand poses, which makes the EMG-based operation difficult. Therefore, it is important to choose a suitable set of hand poses that not only meet the grasping requirements in ADL, but also are differentiable using the EMG signals.

One promising solution to overcome the problem with recognizing the grasping mode is to take advantage of compliant actuators in operation of the hand orthosis. In fact, humans actively take advantage of compliance in digit joints. While grasping an object, the hand poses are determined not only by the kinematics control of digit joints, but also by the stiffness of digit joints and the shape of object [12]. If a hand orthosis has compliance in actuation, a subject wearing the orthosis may grasp many different objects without generating specific hand poses for each object (Fig. 4). Furthermore, this idea may abate the challenge of classification of EMG signals, as the classification algorithm would not need to classify EMG signals into many different grasping modes. The assistive device used in this study has compliant actuation enabling the use of fewer target hand poses [13], [14], [15].

In our previous study [13], the development of a hand exoskeleton for assistance of SCI patients was presented. In this study, we make the following two general contributions. First, we present a methodology to determine a minimal set of target hand poses for compliant assistive hand orthoses that is sufficient for grasping daily objects. Second, we present a method for determining the optimal set and location of sEMG sensors for EMG-based intention recognition to classify user's intent into one of the essential target hand poses.

The paper is structured as follows. In section II, we demonstrate the most-used hand poses in ADL according to literature [11], [10]. Then we present a method to determine a minimal set of essential hand poses required to grasp daily objects using a compliant hand exoskeleton. In section III, we present how we find the optimal locations of sEMG sensors for SCI patients to generate the required command for differentiating between the essential hand poses. We conduct experiments with different number of sensors and combinations. Finally, we determine a minimal set of sensor locations to reliably control the assistive device. Section IV presents conclusions, and potential for application of the results in designing and controlling hand assistive orthoses.

II. TARGET HAND POSES

In this section, we present how the target hand poses of the compliant hand orthosis were determined. The target hand pose is defined as the hand pose generated by a hand orthosis when the hand is relaxed and does not interact with an external object. While using a compliant hand exoskeleton, the actual hand pose might be different from the commanded target hand pose, based on interaction with the object and

(a) Transverse volar grip   (b) Spherical volar grip

(c) Lateral pinch   (d) Diagonal volar grip

(e) Extension grip   (f) Tripod grip
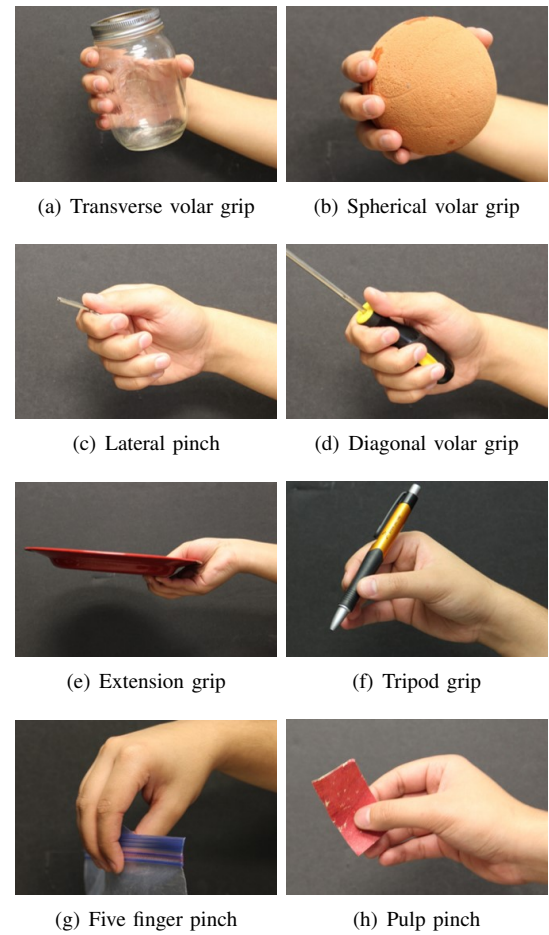
(g) Five finger pinch   (h) Pulp pinch

Fig. 2. Sollerman et al. selected eight most frequently used grips in ADL [11].

the amount of force user generates on their digits. Before explaining the detailed process of answering the question, we first present the background information that will be used, including an overview of the assistive device and definition of ADL based on a study by Sollerman et al. [11].

A. Hand Exoskeleton: Maestro

The exoskeleton used in this study is called Maestro and it has attributes to serve as an active assistive hand orthosis for our purpose. Maestro [13] consists of three finger modules for index finger, middle finger and thumb (Fig. 1). It has four DoF for the thumb and four DoF for the index [14] and middle fingers in total. Therefore, it is capable of providing different hand poses used in ADL. Also, it takes advantage of compliant actuation by implementing series elastic elements between an electric motor and exoskeleton joints [13], [14], [15], allowing for the grasp of objects of different shapes by using only a limited number of hand poses (Fig. 4). It is light and comfortable and it preserves the sensation on finger tips for interaction with objects. In this study, the orthosis is controlled by sEMG signals from the user's muscles (Fig. 3).

B. Representative Objects for ADL

The main goal of an assistive hand orthosis for SCI, is to assist the subjects to perform hand functions in ADL. The first step is to define ADL systematically. The hand functions of ADL has been studied by several researchers [10], [11], [16]. Among those, the study conducted by Sollerman et al. [11], is one of the most extensive studies that focused on the essential hand functions of tetraplegic patients in ADL. Also, the study provides a systematic evaluation method for hand function for the SCI subjects.

Sollerman and Ejeskär [11] selected the most frequently used eight grips in ADL which are transverse volar grip, spherical volar grip, lateral pinch, diagonal volar grip, extension grip, tripod grip, five finger pinch, and pulp pinch as shown in Fig. 2. Then they selected a set of objects that represent objects used in ADL and need the eight grips mentioned.

Among these objects, we excluded several objects that required the exact same grips and we choose a set of 15 objects that required the eight essential grips of ADL. We selected the grasping of following objects as representatives of grasps in ADL: key, wooden block, iron, screw driver, nuts, jar lid, knife, socks, pen, paper, paper clip, telephone, door handle, pure-pak, and cup. Grasping of coins and a water jug is excluded because they required similar grips as a paper clip and an iron, respectively.

C. Methodology for Determining Minimal Set of Target Hand Poses

In this section, we present a method to find a minimal set of target hand poses for an assistive orthosis which would be capable of grasping the objects listed in the previous section. We designed an experiment to test and verify successful grasping of the objects by the minimal set of target hand poses. The basic idea of the experiment is that a researcher increases the number of target hand poses or replaces a target hand pose with another until the subject is able to grasp all 15 objects using the correct grip mentioned in [11]. Two healthy subjects and one SCI subject participated in the experiment, and the results were consistent through all subjects.

The experiment was conducted with the following protocol. First, Maestro is adjusted to optimally fit the given participant. A researcher adjusts the link lengths until the maximum range of motion is achieved while ensuring the
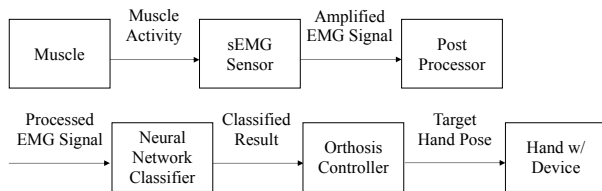

Fig. 3. Signal flow of the muscle activities to the target hand poses of the exoskeleton. The EMG signals are measured and amplified by surface EMG sensors, the amplified signal is post-processed with several filters and classified into a target hand pose of the orthosis with an Artificial neural network classifier.

comfort. Second, the subject is asked to relax their hand. This ensures that grasping an object is performed solely by Maestro. Third, a researcher places an object at a comfortable location within reach of the subject. This eliminates effects from external environments. Fourth, using a computer program a researcher generates a target hand pose in Maestro which is desired to grasp the object. Fifth, the subject with Maestro grasps the object. The subject is allowed to move their arm and shoulder to help his/her hand grasp the object. Sixth, a researcher judges if the subject grasps the object, without dropping and using a correct grip according to [11].

As a first trial, we tried two target hand poses that included transverse volar grip and extension. The results show that, the subjects could not make all hand grips which require thumb adduction (e.g., key pinching). In the second trial, we added lateral pinch to transversal volar grip and extension. With this addition, we enabled the subjects to grasp many objects requiring thumb adduction such as a key and screw driver, but still it was insufficient for grasping flat or small objects such as a nut, paper clip, or piece of paper. Lastly, we added extension grip into the previous set, and subjects were able to grasp all 15 objects listed in [11]. Fig. 4 shows the result of an experiment with a C5/C7 incomplete SCI subject who is barely able to generate flexion force on his index and middle fingers.

The experiment results show that a subject wearing a compliant hand orthosis is able to grasp objects in ADL with the correct grip, using only four hand poses (Fig. 4). The four hand poses include transverse volar grip, lateral pinch, extension grip, and extension, which is a significantly smaller number than the number of hand grips reported in previous grasp studies ([10], [11], [16]).

D. Discussion on Target Hand Poses with a Compliant Exoskeleton

We based our study on previous literature to determine objects and grasps that represent ADL grasping needs. Results of a study by Sollerman et al. [11] were used to understand the most common grasps poses used by humans during daily activities. Then we selected a number of objects used in [11] followed by feedback from SCI subjects in [13] to represent daily objects. Compliance of the assistive orthosis allowed us to further categorize the essential hand poses used in ADL to four major hand poses. Experimental results showed that the four hand poses enabled subjects to grasp all the objects selected from [11] (Fig. 4). However, there are several discussion points about the grasping experiment results.

First, since the compliance of the actuation system allows for the high flexibility in target hand poses, the selected set of hand poses might not be a unique solution. A variation of the selected hand poses can also make an acceptable set of target hand poses for controlling the orthosis. However, the number of the required hand poses to grasp all objects may not be reduced further because as shown in [10], there is a clear requirement of thumb abduction and adduction motion depending on the object's shape. The position of the fingers is also highly dependent upon the object's shape which justifies

Fig. 4. A C5/C7 incomplete SCI subject, who is barely able to generate flexion of index and middle fingers, was able to grasp 15 objects listed in Sollerman hand function test. In the experiment, only four target hand poses of Maestro were used.

having at least two target finger poses at thumb abduction, namely PIP flexion and PIP extension.

Another point we want to emphasize is the difference between grasping an object and performing a task with the object. In this study, we conducted a grasping test in which a subject was able to hold the objects with correct grip and a researcher determined the success of the grasp. Although subjects in this experiment were able to grasp all 15 objects listed in [11] using the four target hand poses, the success in grasping does not guarantee the subject would be able to perform a task with the object. Indeed, the successful fulfillment of a task is achieved only when many complex components meet sufficient conditions including dexterous shoulder and arm function, adequate grasping force, creativity in performing the task, and psychological effects like motivation. Improvement and assessment of the overall hand function of SCI subjects in the task performance has been the focus of a previous study [13]. Furthermore, grasping performance can be improved by implementing active compliance control as well as proportional grasping force control.

In summary, determining the essential grasping poses required in ADL, is a key concern in developing assistive hand orthoses, since the orthosis is required to help patients accomplish ADL. Simultaneously, classification of different hand poses based on intention recognition methods (e.g. EMG, EEG) or even mechanical or speech controlled methods, gets increasingly harder by increasing the number of hand poses. In particular, for sEMG-based intention recognition, by increasing the number of target hand poses, similar patterns might be measured for comparable grasps and classification will get more difficult. Therefore, it is important to discern the minimal set of target hand poses for ADL as it will also be beneficial in increasing the success ratio of EMG classification.

III. LOCATION OF SURFACE EMG SENSORS

In the previous section, we found a minimal set of required target hand poses in ADL for a compliant assistive hand

TABLE I
SIX MUSCLE CANDIDATES TO BE MONITORED BY sEMG SENSORS

Muscle No.	Muscle Name	Innervation
1	Flexor digitorum superficialis	Median nerve (C7, C8 and T1)
2	Extensor digitorum	Posterior interosseous nerve (C7 and C8)
3	Flexor pollicis brevis	Recurrent branch of median nerve (C8 and T1)
4	Flexor carpi ulnaris	Ulnar nerve (C7 and C8)
5	Extensor carpi ulnaris	Posterior interosseous nerve (C7 and C8)
6	Flexor pollicis longus	Anterior interosseous nerve from median nerve (C8 and T1)

orthosis. In this section we present a method to find the optimal locations to attach the sEMG sensors to reliably carry out intention recognition in order to categorize user's intent into one of the four hand poses.

A. Choosing Candidate Sensor Locations

For determining the locations of sEMG sensors, several points need to be considered. First, the muscles monitored by EMG sensors need to be relevant with the four target hand poses. This reduces the training time and makes operation of the device more intuitive. Second, the innervation of muscles from spinal cord need to be considered. For instance, the muscles innervated by upper parts of spinal cord are more suitable because, SCI patients have less function in muscles innervated from lower parts of spinal cord, for instance, intrinsic hand muscles. Third, the target muscles need to be located close to the skin. Otherwise, the signals would be polluted by external electric noise and interfered by signals from other muscles. Fourth, the number of EMG sensors need to be minimized. Using numerous sensors may provide a considerable amount of information, but simultaneously the application with the many sensors is not feasible in
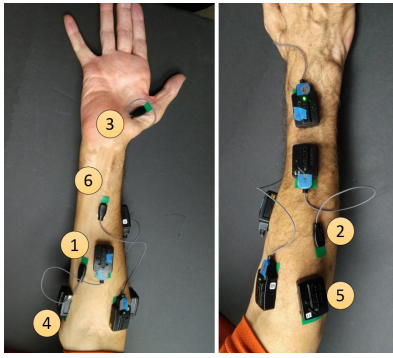
Fig. 5. Six sEMG sensors were attached on a subject's forearm and palm to measure the muscle signals of 1) Flexor digitorum superficialis, 2) Extensor digitorum, 3) Flexor pollicis brevis, 4) Flexor carpi ulnaris, 5) Extensor carpi ulnaris, and 6) Flexor pollicis longus.

reality. For example, Liu et al [17] performed a successful EMG-signal classification with 57 sEMG sensors for SCI subjects. The study showed potential of using sEMG sensors to understand the intention of SCI patients. However, it is difficult to directly implement this sensor configuration in ADL due to high cost and long setting and calibration time. We also consulted with an occupational therapist to understand common muscle patterns of incomplete SCI and available muscles of SCI patients with limited hand function.

Based on the above factors, we selected six candidates of sensor locations to be monitored. We picked target muscles based on relevance to task and muscle innervation. Then we tested the pattern recognition algorithm with different combinations of located sensors to find out the minimal number and location of EMG sensors for achieving reliable control.

The muscles are listed in Table. I. Flexor digitorum superficialis and Flexor carpi ulnaris are selected mainly for detecting the finger motion. Extensor digitorum and Extensor carpi ulnaris are selected mainly for finger and thumb extension. Flexor pollicis brevis and Flexor pollicis longus are selected to detect thumb abduction and flexion. Because the muscle and tendon configuration is correlated with multiple digit joint motions, it is difficult to build a one-to-one match between a joint motion and a muscle. Also due to the characteristics of sEMG sensors, each sensor measures not only a targeted muscle activity but also the activities of other muscles located around that muscle.

Based on these six muscles, we selected six candidate locations for sEMG sensors as shown in Fig. 5. The numbers in the figure correspond to the muscle numbers of Table. I. The quality of the measured EMG signals is crucially dependent on choosing the correct location of sEMG sensors. The occupational therapist assisted us in locating the selected muscle bellies by palpating patient's forearm and palm. Multiple small muscles exist together in the small region of the third sensor (palm), so the third sensor measures activities of Abductor pollicis brevis in addition to the target muscle, Flexor pollicis brevis. However, this was not a problem in the experiment since our goal was to determine user's intent,
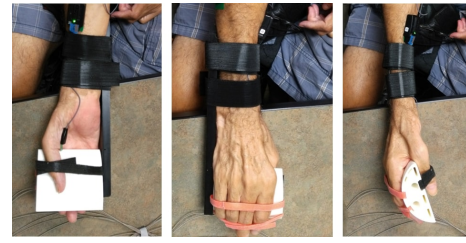

Fig. 6. Maximum voluntary isometric contraction of muscles is measured with a custom made splint. Because SCI patients are not capable of moving their hands, we developed a custom splint to facilitate the measurement.
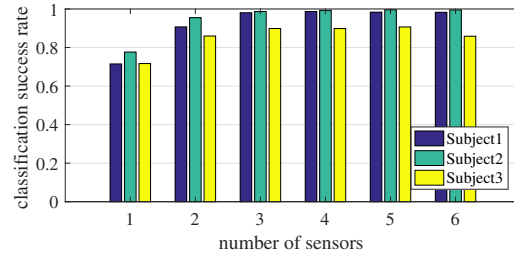

Fig. 7. Maximum EMG-classification success ratios are shown for the three subjects versus different number of sensors. Subject 1 and 2 are healthy subjects and subject 3 is a C5/C7 SCI patient. Success ratio does not vary significantly by increasing sensor numbers after 3 sensors.

not to monitor the single muscle activities.

B. Methodology for Determining Suitable Sensor Locations

We performed an experiment with the following protocol to determine the optimal set of SEMG sensor locations that provide sufficient success ratio for EMG classification. First, six Delsys Trigno™ Wireless EMG sensors are attached on subject's right forearm and palm (Fig. 5). Then the subject's hand is secured in a hand splint and maximum voluntary contraction (MVC) is measured by asking him to perform maximum finger flexion, finger extension and thumb flexion, while muscle activities are being displayed to the subject on a computer screen (Fig. 6). The MVCs measured in this part are used to normalize EMG data in post processing.

For training the EMG classification algorithm, subjects are asked to perform three trials that consist of five tasks interacting with objects including holding a jar (transverse volar grip), holding a key (lateral pinch), holding a plate (extension grip) (Fig. 2), relaxing the hand and extension of fingers and thumb. Subjects are asked to perform each grasp mode for 10 seconds with 10 seconds of relaxation between grasps. To eliminate the effects of transitioning between grasp modes, the two seconds at the beginning and end of each grasp is disregarded and only the midmost 6 seconds of EMG data is used to train classification algorithm. It is important to note that, relaxing of the hand is also considered as one class in EMG classification, in order to help users operate the device without having to exert force throughout the entire grasping motion [13].

EMG data are measured and post processed using the following method [4], [13]. First, the offset is removed
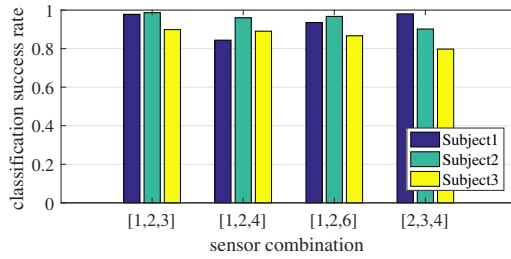
Fig. 8. Success ratios for EMG-classification are shown for four different combinations of sensor locations. Sensor numbers are according to Fig. 5. Subject 1 and subject 2 are healthy subjects and subject 3 is a C5/C7 SCI patient.

and signal is rectified to obtain magnitude values. Then a third order Butterworth low pass filter (cutoff frequency 4 Hz) is applied to produce linear envelope representation of the signal. Next, the signal is normalized to the measured MVC values. This signal is then used as the input to the classification program. According to these signals user's intention is classified into one of five modes, including the four target hand poses and relaxed pose.

From the post-processed EMG data, we created training data sets sampled at 20 Hz to analyze the classification success rates with respect to the sensor configurations. First, we created a total of 60 configurations which are all possible combinations among the six sensors. Second, we created 60 training data sets consisting of the EMG data from the 60 configurations of sensor combinations and the output labels. Third, the 60 classification models with the training data sets were trained. The classification model is developed by an artificial neural network (ANN) algorithm. We selected two-layer feed-forward network with sigmoid hidden softmax output neurons. Fourth, the ANN models were trained with a scaled conjugate gradient back-propagation method. 70% of data were used for training, 15% for validation, and 15% for testing to calculate the success rate of the sensor configuration.

The results of the classified success rates with respect to the sensor configurations have been analyzed. We first selected the highest success rate in the data sets in which the same number of sensors have been used (Fig. 7). We can see that, by increasing the total sensor number, the success ratio is improved and then plateaued after three sensors (Fig. 7). Therefore, we decided to examine the three sensor configurations more closely (Fig. 8).

Among the three sensor configuration, sensor combination (1,2,3) resulted the highest success rates for two cases, and more sensor combinations (1,2,4), (1,2,6), (2,3,4) also resulted in comparably high success rates as shown in Fig. 8.

C. Selecting an Optimal Set of Sensor Locations

Based on the results from last part, we aim to select the suitable set of sensor locations to accomplish intention recognition of the assistive orthosis. There are several discussion points about previous results.

First, the sets of three-sensor combinations with highest success rate were slightly different between subjects. Among the six initial sensor location candidates, we intentionally chose redundant sensor locations for each of the basic finger movements. For instance, sensor 4 monitors the Flexor Carpi Ulnaris, which is responsible for finger flexion similar to Flexor digitorum Superficialis. However, Flexor Carpi Ulnaris is also responsible for wrist flexion. Since, we wanted to avoid coupling of finger and wrist motion while controlling the orthosis, we decided to choose sensor location combination (1,2,3) for extracting sEMG signals for the purpose of determining user's intention among grasp modes.

Secondly, it is important to note that although muscles used in this study have been selected based on hand anatomy and verified through an experiment with two healthy subjects and an SCI subject, they might not be always available in different SCI patients depending on their injury. Target subjects for this method are SCI patients with injury levels between C5 and C8. Nevertheless, there might be patients who do not have sufficient muscle activity in these specific muscle locations for the purpose of intention recognition. In practice, researchers may need to customize the muscle location selection to fit each SCI subject's condition. For SCI patients with severer injuries, sEMG sensors can be moved to muscles that are innervated by higher parts of spinal cord (e.g. biceps, triceps). However, the operation of the assistive device would not be as intuitive compared to using the task-related muscles.

Finally, success ratio range for EMG hand pose categorization among four hand poses, based on the selected muscles, is reported to be around 97% for healthy subjects and 90% for the SCI subject (Fig. 8). One might argue that this success ratio can still cause uncertainty and hazards in practice. However, by implementing the appropriate control method in controlling the assistive orthosis, this success ratio can be improved in operation of the device. For instance, in Maestro [13], the assistive hand exoskeleton used in this study, a stochastic control method is used. EMG signals are monitored within a moving time window and the commanded target hand pose for the device will not execute unless the frequency of the new target hand pose reaches a certain threshold. In addition, in order to eliminate uncertainties caused by fatigue, device can be controlled such that the grasping mode does not change if the subject relaxes his muscles after switching to one hand pose.

IV. CONCLUSIONS AND FUTURE WORKS

In this paper we presented two methodologies to address two of the important challenges in developing and controlling an active assistive orthosis. First method is for determining a minimal set of target hand poses that are essential in ADL for a compliant assistive hand orthosis. We evaluated this selection using objects from a standardized hand function test based on ADL. Second, we present a methodology for determining an optimal set of sEMG sensor locations required for controlling grasping poses of the assistive hand orthosis. Based on experimental results

and anatomy considerations, we selected the minimal set of three sEMG sensors corresponding to Flexor digitorum superficialis, Extensor digitorum and Flexor pollicis brevis to determine the grasping pose. We demonstrated that using EMG signals extracted form these muscles, the system is able to differentiate between the four chosen hand poses with sufficient accuracy.

The outcomes of this study can be used as guidelines for designing and controlling assistive devices. For instance, results of grasping experiment demonstrate that abduction/adduction motion of thumb and flexion/extension motion of thumb and fingers are essential in daily grasp activities. Therefore, it is important to consider the availability and active control of the movements of these degrees of freedom for an assistive hand orthosis. Moreover, by taking advantage of compliance in the design of hand exoskeletons, number of essential target hand poses of the device can be reduced, resulting in easier control of the device. Eventually, we show that for a compliant hand orthosis, a suitable set of only four hand poses is sufficient to grasp objects in ADL.

In addition, using the sEMG signals from task related muscles makes the control of the device more intuitive and easier for the user. Moreover, by increasing the number of target hand poses, intention recognition by sEMG signals becomes more difficult. In order to achieve a reliable control, we used a pattern recognition algorithm, based on all possible combinations of sensor locations to examine the success of the EMG-based intention recognition method. We demonstrated that the success ratio of intention recognition algorithm reaches a plateau and does not improve significantly by adding more sensors beyond a certain limit. Then we selected the optimal combination of sensor locations, based on experimental results and subject conditions, to provide a reliable control. A similar practice can be used to determine the minimal number of bio-signals required to control any other active assistive device.

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