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Subject-specific Myoelectric Pattern Classification of Functional Hand Movements for Stroke Survivors

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Abstract

In this study, we developed a robust subject-specific electromyography (EMG) pattern classification technique to discriminate intended manual tasks from muscle activation patterns of stroke survivors. These classifications will enable volitional control of assistive devices, thereby improving their functionality. Twenty subjects with chronic hemiparesis participated in the study. Subjects were instructed to perform six functional tasks while their muscle activation patterns were recorded by ten surface electrodes placed on the forearm and hand of the impaired limb. In order to identify intended functional tasks, a pattern classifier using linear discriminant analysis was applied to the EMG feature vectors. The classification accuracy was mainly affected by the impairment level of the subject. Mean classification accuracy was 71.3% for moderately impaired subjects (Chedoke Stage of Hand 4 and 5), and 37.9% for severely impaired subjects (Chedoke Stage of Hand 2 and 3). Most misclassification occurred between grip tasks of similar nature, for example, among pinch, key, and three-fingered grips, or between cylindrical and spherical grips. EMG signals from the intrinsic hand muscles significantly contributed to the inter-task variability of the feature vectors, as assessed by the inter-task squared Euclidean distance, thereby indicating the importance of intrinsic hand muscles in functional manual tasks. This study demonstrated the feasibility of the EMG pattern classification technique to discern the intent of stroke survivors. Future work should concentrate on the construction of a subject-specific EMG classification paradigm that carefully considers both functional and physiological impairment characteristics of each subject in the target task selection and electrode placement procedures.

Keywords

Stroke; Electromyography (EMG); Pattern classification; Hand; Functional task

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I. Introduction

Stroke is a primary cause of serious, long-term disability in the United States [1]. While many stroke survivors eventually regain functional use of their lower extremities (e.g. walking, albeit often with the use of an aid), their upper limb recovery is slow and often limited [2,3]. Specifically, hand dexterity is likely to be most affected, and therapeutic treatment usually appears to have limited effect on those with severe impairment [4]. Consequently, recovery of hand function is often limited and chronic deficits persist. Many stroke survivors cannot voluntarily perform functional manual tasks without assistance, mainly due to their weakness [5], spasticity [6], or abnormal muscle coactivation [7]. Due to the importance of the hand in daily activities, the effective restoration of its functionality should be one of the primary goals for stroke survivors.

A number of devices have been developed which could potentially provide assistance for the hand [8-11]. Some of the exoskeleton devices, for example, can assist users in performing functional tasks such as pinch grip [12] or other complex tasks requiring independent control of individual finger joints [13]. A greater challenge for effective task performance, however, lies in providing volitional control of these devices to the user.

One commonly used means of implementing control of external devices is through the use of electromyography (EMG). In the past, this was often done through the mapping of the EMG of a single muscle to control of a single degree-of-freedom (DOF). For example, in myoelectric prostheses, biceps activation might trigger flexion of the prosthetic elbow and triceps activation might trigger elbow extension [14]. Similarly, in stroke survivors, biceps and triceps activation might be used to control elbow flexion and extension, respectively, through a powered orthosis [15]. Alternatively, the EMG signal from a weak muscle could be detected in order to trigger amplified activation of the same muscle [16].

The digits of a hand, however, contain 21 independent DOF. Most functional manual tasks involve complex temporal and spatial coordination of multiple muscles [17,18]. Control of even a subset of these DOF through the single muscle EMG-single DOF is not feasible. To surmount these limitations, research in the field of upper-extremity prosthetics has increasingly focused on the classification of the EMG activity patterns of multiple muscles, and has been successfully performed [19-23]. A number of technical aspects of the EMG classification method, such as electrode placement [24], classification algorithm [25], and signal processing [26], have been extensively investigated to improve the classification performance. Some recent EMG classification techniques explored the potential of subject-specific classifier by allowing the users to define their own target movements, and achieved high classification accuracy [27]. Recently, the application of these techniques has been expanded to a spinal cord injury patient population, and an EMG classification technique employing artificial neural network was employed to successfully identify their intent from their remaining ‘voluntary’ muscles, thereby providing necessary inputs for upper extremity neuroprosthesis using functional electrical stimulation [28].

In stroke survivors, however, exploration of the use of EMG pattern classification technique across multiple muscles to identify the intended functional tasks is much more limited. The stroke population presents some unique challenges but also some opportunities in comparison with the population of prosthetics users. In stroke survivors, spasticity, abnormal muscle activation [29], and excessive antagonist coactivation [30], which do not exist in amputees, may hamper accurate classification of muscle activation patterns, specifically for those with severe neurological impairment. For example, activation of a given finger muscle may show limited modulation across a variety of intended finger force directions [31]. Synergistic muscle activation patterns in stroke was found to be distinguished from those obtained from healthy control subjects, as identified by a Bayesian network modeling method for pattern classification [32]. On the other hand, while EMG classification techniques for transradial amputees have targeted only forearm muscles, signals from hand intrinsic muscles are available as inputs in stroke survivors, and their inclusion should be able to greatly enhance accuracy. Therefore, activation patterns of different muscle groups (including hand intrinsic muscles) of stroke survivors and their inter-task and intra-task variability should be carefully analyzed to ensure the successful EMG pattern classification of stroke survivors.

In this study, we present a subject-specific EMG pattern classification technique that discriminates intended manual tasks from the muscle activation patterns of stroke survivors. The specific aims of this study were: (1) to examine inter-task and intra-task variability in muscle activation patterns of stroke survivors, (2) to clarify the contribution of different muscle groups to the inter-task variability of the muscle activation patterns, (3) to elucidate correlation between the subject impairment levels and the inter-task variability of their muscle activation patterns, and (4) to assess the feasibility of the EMG classification technique for identifying the intent of stroke survivors to perform different functional manual tasks, with the intended application of enhanced control of assistive devices. Accurate identification of the intent of stroke survivors by the EMG pattern classification, if successfully implemented, would be able to provide control of assistive device enabling them to voluntarily perform fundamental functional tasks crucial in their daily activities.

II. Methods

A. Subjects

Twenty subjects with chronic hemiparesis (ages 45 – 73 years; 12 males and 8 females; minimum 1 year since the onset of stroke) participated in the study. Subjects were selected based on hand motor impairment level, as assessed by a research occupational therapist. Impairment was classified on an ordinal scale from 1 to 7 in accordance with the Stage of Hand component of the Chedoke-McMaster Stroke Assessment scale. A “1” indicates the most severe impairment and a “7” indicates an ability to perform all of the tasks on the scale [33]. According to the definition of the Hand Stages in the Chedoke-McMaster scale, impairment level of each subject is categorized as a certain stage if he/she can perform more than two tasks listed in that stage. Items for the stage 2 include positive Hoffmann, resistance to passive wrist or finger extension, facilitated finger flexion; for the stage 3, wrist extension > ½ range, finger/wrist extension > ½ range, thumb to index finger; for the stage 4, finger extension then flexion, thumb extension > ½ range then prehension, finger flexion with lateral; and for the stage 5, finger flexion then extension pronation, finger abduction, spherical grip [33].

Five subjects were recruited for each Stage from 2 – 5. Subjects were categorized into two groups according to their impairment level: severely impaired subject group (Stage of Hand 2 and 3) and moderately impaired subject group (Stage of Hand 4 and 5). The experimental protocol was approved by the Northwestern University Institutional Review Board, and informed consent was obtained from each subject.

B. Instrumentation

Ten pairs of disposable, self-adhesive silver/silver chloride surface electrodes (Noraxon, AZ, USA) were used for the surface EMG recording of each subject. Three pairs were placed on the hand, and seven pairs on the forearm. On the hand, the first electrode (E1) was placed on the radial to the first metacarpal (MC) bone to target the thenar muscles, the second (E2) on the radial to the second MC to target the first dorsal interosseous muscle (Fig. 1a), and the third (E3) on the ulnar to the fifth MC to target abductor digiti minimi (Fig. 1b). One electrode (E4) was placed on the groove of the posterior side of the forearm where the radius, ulnar and lunate bones meet. Six electrodes (E5-E10) were placed on the forearm at a location 40% of the distance from the medial epicondyle of the humerus to the styloid process of the ulna. These six electrodes were equally spaced around the circumference of the forearm (Fig. 1c), as previous studies have suggested that targeted and untargeted electrode placement strategies produce similar classification accuracies [24]. Three of the six electrodes (E5-E7) were placed on the anterior side of the forearm, and three (E8-E10) on the posterior side.

C. Experimental Protocol

Subjects were seated upright comfortably on a chair and instructed to rest their forearm on the table, which was adjusted according to their seated height, and their elbow was flexed to approximately 90°. They were asked to perform the following six tasks or to relax (no movement): hand open, key grip, pinch grip, cylindrical grip, spherical grip, and three-fingered grip (Fig. 2). For grip tasks, objects were placed in their hand by the experimenter. Specialized MATLAB-based software (ACE, Neural Engineering Center for Artificial Limbs, Chicago, IL) was used to guide subjects throughout each session. This software provided each subject with visual feedback regarding target task and task initiation/termination time, recorded EMG signals during each task performance.

Subjects participated in three sessions (Fig. 3) on one day. In each session, subjects were asked to perform seven tasks (six functional tasks + no movement). During each session, two blocks of these seven tasks were performed to train the classifier system (Classifier training session 1 – 3 in Fig. 3). For each task, subjects were asked to hold the object with moderate grip force for 3 – 5 seconds. Between tasks, brief relax/preparation periods were given to help the stroke survivors to relax, to decrease muscle spasticity resulting from each task performance, and to prepare for the next task. The length of the preparation period was adjusted to a value between 7 and 20 seconds, according to the impairment level of each subject. The duration of the preparation period (rest time) was determined from a preliminary experiment performed prior to this study. In this pilot work, we examined how much time would be required for each subject to change between grip tasks. Generally, for moderately-impaired subjects, 5-10 seconds of the preparation period between grip tasks was sufficient, whereas at least 10-15 seconds were required for the subject with severe impairment in order for them to open the hand, release the object, and prepare to perform the next grip task.

Classification performance was measured in two evaluation sessions, the first of which took place after the 2nd training session, and the second after the 3rd training session (Classifier evaluation session 1 – 2 in Fig. 3). In each evaluation session, the seven tasks were presented in a random order, twice per task. The entire experiment took approximately 2 to 3 hours to complete.

D. Classifier

In the classifier training sessions, pattern classification was performed on segments of the data. Data analysis windows were 150 ms in duration shifted in 100 ms increment (i.e. overlap of 50 ms). For each analysis window, four sets of features from time-domain statistics of the EMG signals were computed, mean absolute value (MAV), the number of zero crossing (ZC), the slope sign change (SSC), and the waveform length (WL) [20] (see Appendix). These time-domain features were used since these features can be estimated with less computational cost, but still yield classification performance similar to that of more complex feature sets, such as Fourier transform, wavelet transform, and autoregressive coefficients [34]. The feature set was computed on each of ten EMG channels, and these feature sets were concatenated to a 40-dimensional feature vector and provided to train a subject-specific linear discriminant analysis (LDA) classifier [35]. LDA was selected over other types of classification methods due to its ease of implementation and its faster training process. It was reported in previous studies [34,36] that LDA does not compromise the classification accuracy when compared to other types of more complex classifiers.

Here, note that, from the EMG data collected from one three-second task performance, 30 feature vectors were calculated (100 ms increment over 3 seconds). Therefore, 60 feature vectors for each task were collected during each training session.

In the classifier evaluation sessions, pattern classification was performed on data analysis windows, which were 150 ms in duration (t_{L1}) shifted in 100 ms increments (i.e. overlap of 50 ms). In each evaluation session, a subject-specific LDA classifier constructed in the preceding training session was applied to discern the intent of the stroke survivors. It should be noted that the training data accumulated over the training sessions were combined into a single training set. In other words, the classifier used in the Classifier evaluation session 1, which took place after the Classifier training session 2, was built based on the EMG data collected in the training session 1 and 2, and the classifier in the Classifier evaluation session 2 was constructed using the entire EMG data set collected in all three training sessions (Classifier training session 1 – 3) (Fig. 3).

E. Data Analysis

Performance of subject-specific EMG pattern classifier—In order to evaluate the performance of the subject-specific classifier, classification accuracies were calculated in the two evaluation sessions for each subject (Fig. 3). Confusion matrices, whose elements indicate incidence rates of correct and false classifications, were calculated in order to delineate the classification performance of subject-specific classifiers. A two-way analysis of variance (ANOVA) was performed to examine the effects of the two variables, i.e. the subject impairment level and the number of training sessions, on the classification accuracy.

Inter-task and intra-task variability of muscle activation patterns—Inter-task and intra-task variability of muscle activation patterns of each stroke survivor were examined based on the EMG feature vector data collected in the two evaluation sessions (7 task × 2 task performances/session × 2 sessions = total of 28 task performances). In order to quantify the degrees of inter-task and intra-task variability, squared Euclidean distance (SED) matrix, **D**, between the feature vectors of the seven tasks (six manual task and rest) were calculated. In addition, in order to clarify the contribution of different muscle groups to the inter-task variability, SED matrices were estimated from the feature vectors of each of the following three subsets of muscles, 1) hand intrinsic (HI) muscles (E1-E3), 2) forearm anterior (FA) muscles (E4-E7), and 3) forearm posterior (FP) muscles (E8-E10; see section 2.B). Accordingly, three SED matrices that represent inter-task variability of the three muscle groups, $\mathbf{D}_{HI}$, $\mathbf{D}_{FA}$, $\mathbf{D}_{FP}$, were estimated as follows:

$$\mathbf{D}_{HI}=\begin{bmatrix} d_{11}^{HI} & \cdots & d_{17}^{HI} \\ \vdots & \ddots & \\ d_{71}^{HI} & & d_{77}^{HI} \end{bmatrix}, \mathbf{D}_{FA}=\begin{bmatrix} d_{11}^{FA} & \cdots & d_{17}^{FA} \\ \vdots & \ddots & \\ d_{71}^{FA} & & d_{77}^{FA} \end{bmatrix}, \mathbf{D}_{FP}=\begin{bmatrix} d_{11}^{FP} & \cdots & d_{17}^{FP} \\ \vdots & \ddots & \\ d_{71}^{FP} & & d_{77}^{FP} \end{bmatrix} \quad (1)$$

where

$$d_{ij}^{HI}= \|\bar{\mathbf{f}}_i^{HI} - \bar{\mathbf{f}}_j^{HI}\|_2, d_{ij}^{FA}=\|\bar{\mathbf{f}}_i^{FA} - \bar{\mathbf{f}}_j^{FA}\|_2, \quad \text{and} \quad d_{ij}^{FP}=\|\bar{\mathbf{f}}_i^{FP} - \bar{\mathbf{f}}_j^{FP}\|_2 \quad (i \neq j)$$

$$d_{ii}^{HI}= \frac{1}{N}\sum_{k=1}^{N}\|\mathbf{f}_i^{HI}(k) - \bar{\mathbf{f}}_i^{HI}\|_2, d_{ii}^{FA}=\frac{1}{N}\sum_{k=1}^{N}\|\mathbf{f}_i^{FA}(k) - \bar{\mathbf{f}}_i^{FA}\|_2, \quad \text{and} \quad d_{ii}^{FP}=\frac{1}{N}\sum_{k=1}^{N}\|\mathbf{f}_i^{FP}(k) - \bar{\mathbf{f}}_i^{FP}\|_2$$

Here,

$\mathbf{f}_i^{HI}(k)$: 12-element EMG feature vector of task *i* at k^{th} task performance estimated from three channels recording HI muscle activities (E1-E3) (k = 1, 2, 3, 4; 2 task performances × 2 sessions)

$\bar{\mathbf{f}}_i^{HI}$: Mean EMG feature vector of task *i* (HI muscles) averaged across all 4 task performances

$\mathbf{f}_i^{FA}(k)$: 16-element EMG feature vector of task *i* at k^{th} task performance estimated from three channels recording FA muscle activities (E4-E7) (k = 1, 2, 3, 4)

$\bar{\mathbf{f}}_i^{FA}$: Mean EMG feature vector of task *i* (FA muscles) averaged across all 4 task performances

$\mathbf{f}_i^{FP}(k)$: 12-element EMG feature vector of task *i* at k^{th} task performance estimated from three channels recording FP muscle activities (E8-E10) (k = 1, 2, 3, 4)

$\bar{\mathbf{f}}_i^{HI}$: Mean EMG feature vector of task *i* (FP muscles) averaged across all 4 task performances

Each off-diagonal element (i, j) of each SED matrix, d_{ij} provides a quantitative measure for the inter-task variability (i.e. distance inter-task variability) between task *i* and task *j*, while the i^{th} diagonal component, d_{ii}, denotes a quantitative intra-task variability of the task *i*.

III. Results

A. Classification Accuracy/Performance

Average classification accuracies across 1) subject impairment level, and 2) number of training sessions are summarized in Table 1. The average classification accuracy was 37.9% for highly impaired subjects (Chedoke Stage of Hand 2 and 3), and 71.3% for moderately impaired subjects (Chedoke Stage of Hand 4 and 5). The classification performance was significantly different across subjects with different functional impairment levels (i.e. Chedoke-McMaster score) ($p < 0.01$). A grand mean of the classification accuracy across all subjects and all experimental conditions was 54.6%. ANOVA revealed that the number of training sessions did not significantly affect the classification accuracy ($p > 0.45$). Interaction between these two variables, the impairment level and the number of training sessions, was not found to be significant ($p > 0.45$).

Generally, subject-specific classifiers were able to distinguish different grip tasks performed by moderately impaired subjects (Chedoke Stage of Hand 4 and 5), although there was some difficulty discriminating between similar grasps, specifically between pinch grip and three-fingered grip and between spherical grip and cylindrical grip, which can be also observed in the representative classification performances presented in Fig. 4a. For severely impaired subjects (Chedoke Stage of Hand 2 and 3), larger number of misclassifications between grip tasks were generally observed (Fig. 4b).

Confusion matrices, which display the frequency of correct and misclassification incidences in the evaluation sessions, were estimated to summarize the classification results across the different tasks (Table 2). For both subject groups, the highest number of misclassifications was observed between cylindrical and spherical grip tasks, followed by misclassifications between pinch and key grip tasks. Overall, higher incidence rate of misclassifications between grip tasks was observed in severely impaired subjects (Table 2b). In severely-impaired subjects, hand open tasks were often confused with no movement. In both subject groups, three-fingered grip task resulted in the lowest classification accuracy (54.8% for moderately-impaired subjects, and 23.0% for severely-impaired subjects).

B. Inter-task and intra-task variability of muscle activation patterns

Estimated SED matrices indicated that inter-task variability values between most grip tasks were considerably higher than their intra-task variability values in moderately-impaired subject groups (Table 3a); however, in severely-impaired subjects, inter-task variability values between similar types of grip tasks were similar to the intra-task variability values (Table 3b). Inter-task variability values between similar type of grip tasks, specifically between cylinder grip (CG) and spherical grip (SG), and pinch grip (PG) and key grip (KG) were found to be similar to or smaller than the intra-task variability values (i.e. diagonal elements of the confusion matrices), which explains higher misclassification incidence rates between these tasks. SED values between the three-fingered grip and other grip tasks were generally small. Among the three muscle groups, inter-task variability values estimated from the hand intrinsic muscles ($\mathbf{D}_{HI}$) was the largest (Table 3c,d vs. e-h).

In order to explain the low classification accuracy in severely-impaired subjects, EMG signals from the three hand muscles/muscle groups of these subjects and their inter-task variability were qualitatively assessed (Fig. 5). In the subjects with low classification accuracies, activities of these intrinsic hand muscles (Electrode 1, 2 and 3; see Fig. 1a) were found to be generally either weak (Fig. 5b) or changed approximately with the same proportion according to the task (Fig. 5c), whereas the muscle activation patterns were relatively distinct across tasks in moderately impaired subjects (Fig. 5a).

IV. Discussion

Classification of intended manual tasks was performed from EMG data obtained from individuals with chronic hemiparesis following stroke. Subjects performed 7 different tasks: hand open (HO), key grip (KG), pinch grip (PG), cylindrical grip (CG), spherical grip (SG), three-fingered grip (3G), and relax (NM). The number of classifier training sessions (i.e. amount of training data) was not found to significantly affect the classification accuracy. The accuracy tends to increase with more classifier training sessions (Table 1), but these improvements did not reach statistical significance ($p > 0.45$). Thus, training could be performed in a relatively short time (4 performances per task).

The classification accuracy was mainly affected by the subject's functional impairment level, as rated according to the Chedoke-McMaster scale (Table 1). Classification ranged from 33.5% accuracy for severely impaired subjects at Stage 2 to 77.4% accuracy for moderately impaired subjects at Stage 4. The diminished classification accuracy for the severely impaired subjects seemed to result from the reduced signal-to-noise ratio in the EMG signals (due to reduced signal strength) and an inability to independently modulate muscles with task – in other words, EMG signals from different muscles changed with the same proportion across tasks (Fig. 5c). It should be noted that generally larger (trial-to-trial) variability in EMG signals was observed in stroke survivors compared to neurologically unimpaired subjects. Therefore, EMG data obtained from amputees, who often have no further neurological damage than the amputation, would provide more uniform and stable muscle activation data, allowing various signal features (for example, time-domain and frequency-domain features) and classifier types (such as LDA, fuzzy logic, and neural network) to be tested for optimizing classifier performance.

Previous studies reported that functional manual tasks require accurate control of not only large extrinsic muscles (e.g. flexor digitorum profundus) but also intrinsic hand muscles (e.g. dorsal interosseous, lumbrical, flexor pollicis brevis, abductor pollicis brevis, etc.) [17,37]. Since the control of distal muscles tends to be more impaired in stroke survivors [38], many subjects, specifically severely impaired subjects, seemed to have more difficulty in controlling these intrinsic muscles during different grip tasks (Fig. 5b and 5c).

For moderately impaired subjects, however, EMG signals from the intrinsic hand muscles did increase the inter-task distance considerably, thereby promoting accurate task classification, as indicated by the increase in the inter-task squared Euclidean distance (SED) values (Table 2). For these subjects, these inter-task SED values of the feature vector were generally larger than the intra-task variability of the feature vector ($0.41 \times 10^6 < d_{ii} < 0.68 \times 10^6$; Table 3), which indicates the inherent variability of the EMG feature vector within each task; note that, however, the SED values between some tasks of very similar nature were still relatively small (e.g. between spherical grip and cylindrical grip; see Table 3). In general, for many moderately impaired subjects (Chedoke Stage of Hand 4 and 5), subject-specific classifiers were able to distinguish different intended functional grip tasks. Thus, EMG signals from the intrinsic hand muscles should be utilized in the EMG pattern classification of grip tasks performed by stroke survivors, although some practical limitations should be considered; for example, some electrodes placed on the hand muscles, depending on their location, might interfere with the given manual task.

Although the classification performance was relatively poor in highly impaired subjects, subject-specific classifiers for most of these stroke survivors were able to distinguish tasks of different nature, for example, hand open vs. grip tasks. Note that most misclassification in moderately impaired subjects occurred only between similar types of grip tasks, i.e. between spherical and cylindrical grips, or between pinch and key grips (Fig. 4a; Table 2b). Two of these tasks, cylindrical and spherical grips, can be categorized as 'power grasp-type' tasks, and three of these tasks, key, pinch, and three-fingered grips, as 'pinch-type' tasks. While discrimination accuracy among the entire set of target tasks was relatively low, discrimination accuracy among distinct types of tasks (i.e. power grasp, pinch, and hand open) was high. In a supplementary analysis in which only 4 categories (open, no movement, pinch, power grasp) were used instead of original 7 tasks, we found that the classification accuracy was much improved. Classification accuracy across this set was 56.7% for highly impaired subjects, and 89.3% for moderately impaired subjects (overall classification accuracy = 73.0%).

The results of this study strongly suggest that the EMG pattern classification system for stroke survivors should be designed specifically for each subject. The selection of target tasks (number and complexity), for example, should reflect the functional impairment level of each subject. For severely-impaired subjects, using fewer, more distinct tasks (i.e. hand open, power grasp, and pinch) would produce more favorable outcomes than using more tasks with may be difficult to discriminate. Also, electrode placement strategy should consider the motor control characteristics of each subject; for instance, if a subject maintains the control of intrinsic hand muscles, the classification system should utilize those muscles. For those who cannot control intrinsic muscles, in contrast, the system should focus on more proximal muscles (i.e. forearm muscles) in order to extract useful signals for task classification. Age of the subjects should be considered in the design of subject-specific EMG classification systems, since the changes due to aging in strength, fatigability, and signal variability may impact the EMG pattern classification performance significantly.

Some limitations of the study should be recognized. We used untargeted electrode placement strategy for forearm muscles (Fig. 1b) because previous studies found no significant difference in classification performance between targeted and untargeted electrode placement [24]. Additionally, it is difficult to locate individual muscles of stroke survivors who lost control of many muscles due to their motor impairment. However, considering their weakness [5] and consequent weak EMG signals, accurate placement of the electrodes targeting individual muscles may significantly improve the EMG signal quality, thereby improving classification performance. In addition, it should be acknowledged that many muscles of the hand and forearm (specifically thumb muscles) are located relatively deep, and thus cannot be accessed by surface electrodes. Previous studies reported that surface and intramuscular electrodes result in similar classification performance in subjects with no neurological impairment [24,34]. But, since stroke survivors lose control of significant muscles due to their neurological impairment, additional signals from their deep muscles (e.g. flexor digitorum profundus or flexor/extensor pollicis longus) may be able to provide useful supplementary information to the pattern classifier. Nevertheless, note that targeting these muscles may involve additional procedures (e.g. ultrasound guidance), pain and discomfort (percutaneous insertion), or even surgical operations (implanted electrodes). Further investigation will be required to accurately assess both the positive and negative impact of these factors, thus developing efficient and accurate subject-specific EMG pattern classification system for stroke survivors.

V. Conclusion

This study demonstrated the feasibility of the EMG pattern classification technique to discern the intent of stroke survivors performing manual tasks. To our knowledge, this is the first study that employed pattern classification techniques to identify intended functional tasks from the muscle activation patterns of stroke survivors. The proposed EMG classification system was able to distinguish tasks of a distinct nature (i.e. hand open vs. grip tasks), although its classification accuracy for similar grip tasks was relatively low, specifically for severely impaired subjects. Most misclassification occurred between similar types of grip tasks such as cylindrical and spherical grip; however, it should also be acknowledged that, as a pilot study, some tasks of similar nature were purposely included as target tasks. Future work should concentrate on the construction of a subject-specific classification paradigm that carefully considers both functional (for selection of target functional tasks) and physiological (for target muscle selection for EMG channels) impairment characteristics of each subject for target task selection and electrode placement procedures.

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APPENDIX

A. Mean absolute value (MAV): m

$$\mathbf{m}=[m_1 \quad m_2 \quad \cdots \quad m_{10}], \quad \text{where} \quad m_i=\frac{1}{N}\sum_{k=1}^{N}|x_i(k)| \quad (1)$$

Here, $x_i(k)$ is the k^{th} sample of the channel i, and N is the total number of data within each time window.

B. Zero Crossing (ZC): z

$$\mathbf{z}=[z_1 \quad z_2 \quad \cdots \quad z_{10}] \quad (2)$$

For each channel (i = 1, 2 ... 10), given two consecutive samples $x_i(k)$ and $x_i(k+1)$, increment zero crossing count, if

$$x_i(k) \times x_i(k+1) < 0 \quad \text{and} \quad |x_i(k) - x_i(k+1)| < \varepsilon_z \quad (3)$$

Here, ε_z is a threshold value set to reduce noise-induced zero-crossing (in this study, ε_z = 0.025V). Each z_i value was normalized by the total number of data N.

C. Slope Sign Change (SSC): s

$$\mathbf{s}=[s_1 \quad s_2 \quad \cdots \quad s_{10}] \quad (4)$$

For each channel (i = 1, 2 ... 10), given three consecutive samples $x_i(k–1)$, $x_i(k)$ and $x_i(k+1)$, increment slope sign change count, if

$$\{x_i(k) - x_i(k-1)\} \times \{x_i(k) - x_i(k+1)\} < 0 \quad \text{and} \quad |x_i(k) - x_i(k+1)| > \varepsilon_z \quad (5)$$

ε_s is a threshold value set to reduce noise-induced slope sign change (in this study, ε_s = 0.025V). Each s_i value was normalized by the total number of data N.

D. Waveform Length (WL): w

$$\mathbf{w}=[w_1 \quad w_2 \quad \cdots \quad w_{10}], \quad \text{where} \quad w_i=\frac{1}{N}\sum_{k=2}^{N}|x_i(k) - x_i(k-1)| \quad (6)$$

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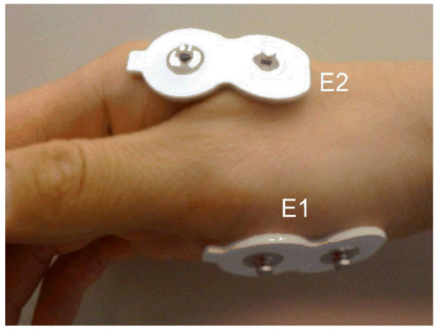
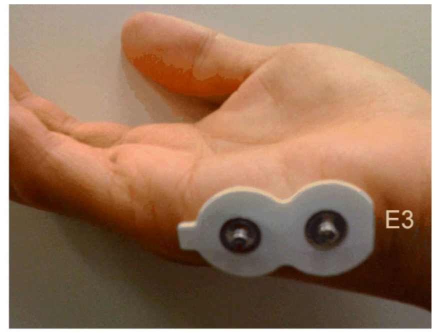
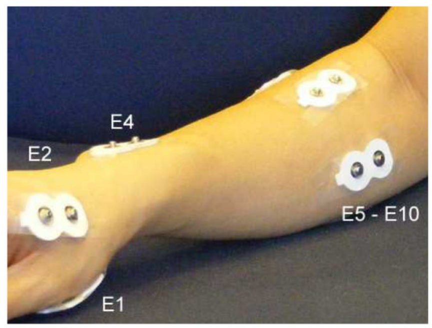




(a) (b)



(c)

Fig. 1.

Electrode placement: (a) and (b) Three electrodes (E1 – E3) targeting hand intrinsic muscles (E1: thenar muscles, E2: first dorsal interosseous, E3: hypothenar muscle) (c) one electrode (E4) placed near the wrist and six electrodes (E5 – E10) on the circumference of the forearm.

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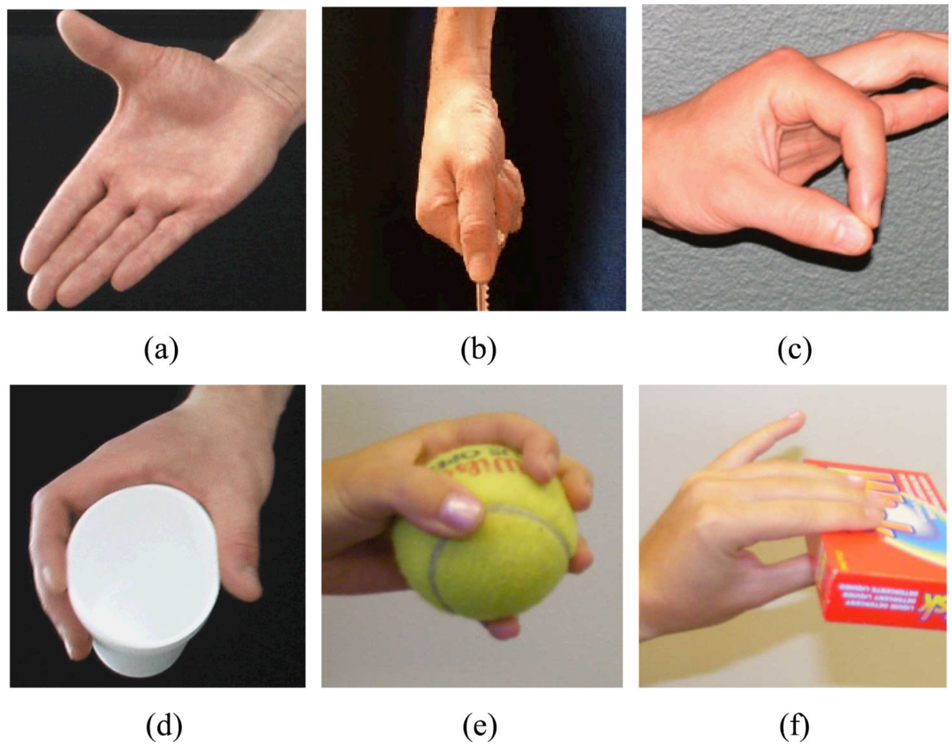


Fig. 2.

Six target tasks: (a) Hand open (b) key grip (c) pinch grip (d) cylindrical grip (e) spherical grip (f) three-fingered grip

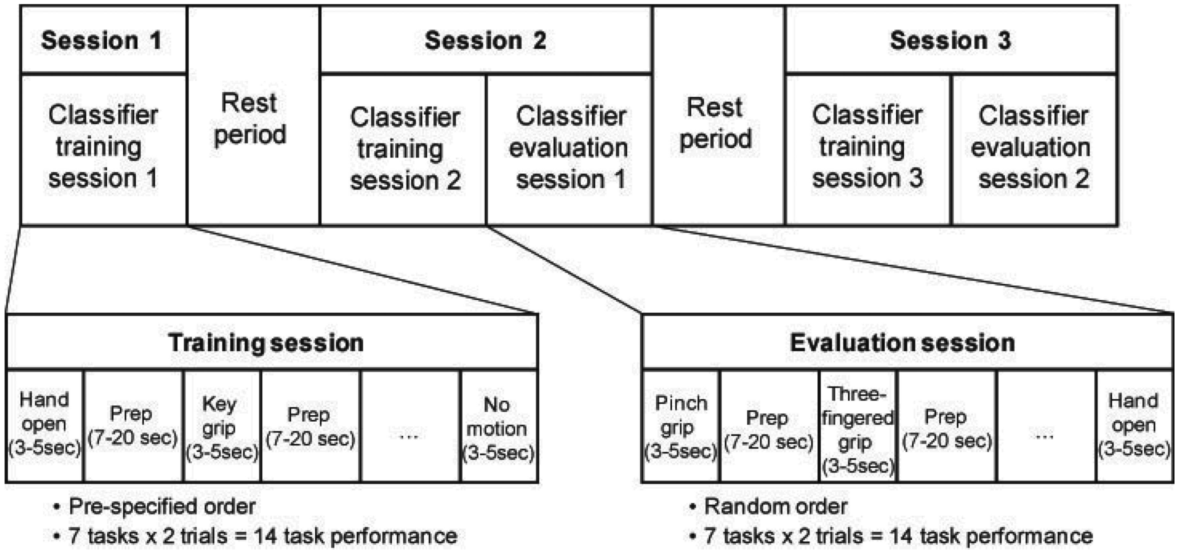
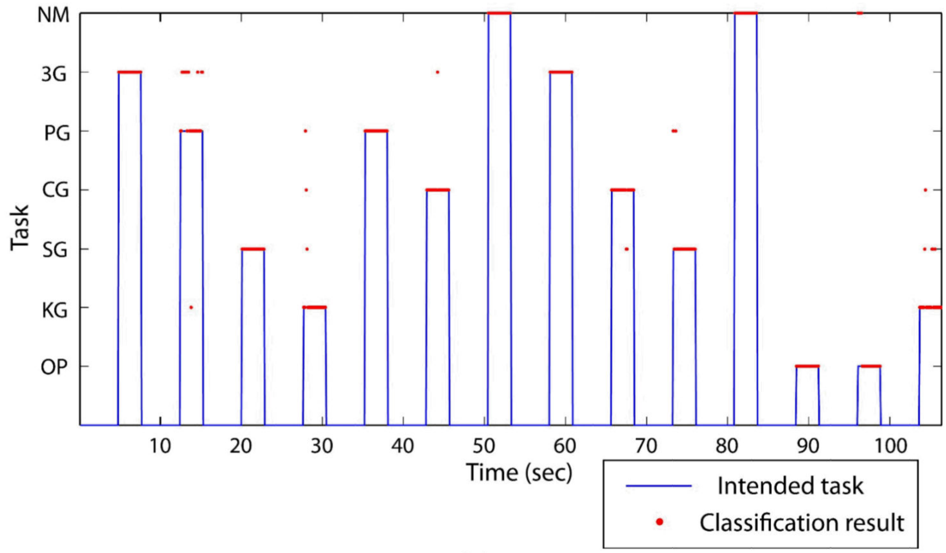
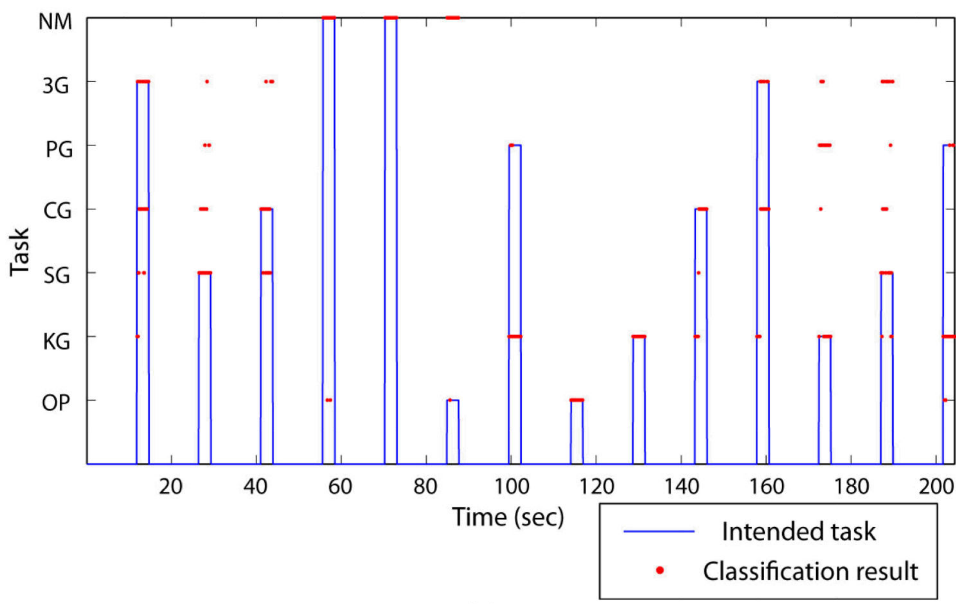


Fig. 3.
Schematic diagram of the experimental protocol.



(a)



(b)

Fig. 4.

Representative real-time classification performances: (a) Moderately impaired subject (Subject 5, Chedoke Stage of Hand 4), and (b) severely impaired subject (Subject 6, Chedoke Stage of Hand 3). Note that longer preparation time was required for the severely impaired subject (~ 20 sec). A higher number of misclassifications between similar grip tasks, e.g. between cylindrical and spherical grip, and between pinch and three-fingered grip, were observed in severely impaired subjects. However, even for severely impaired subjects, misclassification between the tasks of a very different nature (between open and grip tasks) was rarely observed. Open task was often misclassified as no movement, due to their weak extensor activities (Abbreviation: OP; open, KG; key grip, SG; spherical grip, CG; cylindrical grip, PG; pinch grip, 3G; 3-fingered grip, NM; no movement).

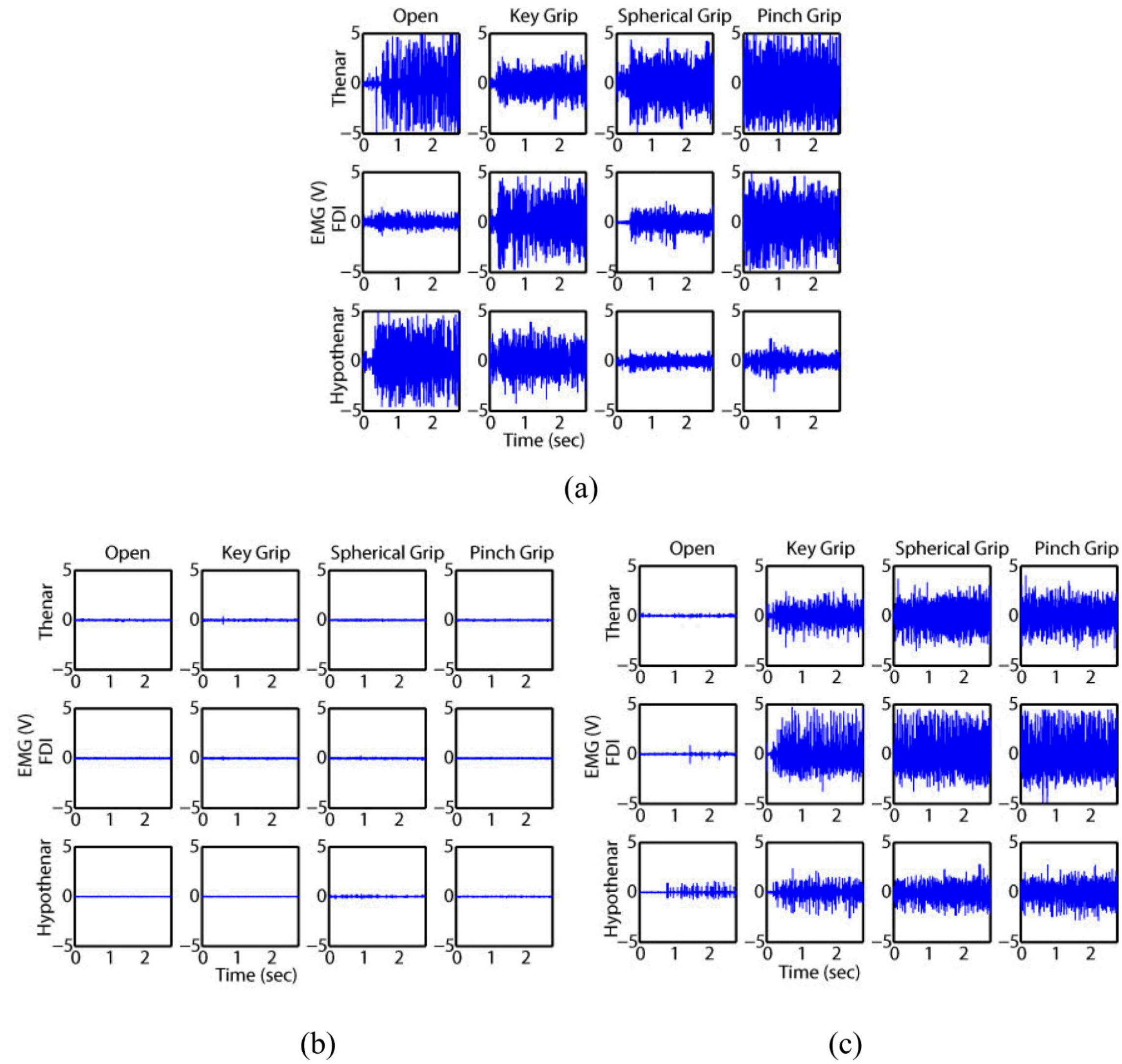


Fig. 5.

EMG signals recorded from thenar, first dorsal interosseous (FDI), and hypothenar muscles across four functional tasks: open, key grip, spherical grip, pinch grip: (a) Moderately impaired subject (Subject 14 – Chedoke Stage of Hand 5) (b, c) severely impaired subjects (b: Subject 7 – Chedoke Stage of Hand 3, c: Subject 17 – Chedoke Stage of Hand 2). Hand muscle activations across different functional tasks showed distinct patterns in the moderately impaired subject (a). However, activities of these distal muscles (i.e. hand intrinsic muscles) of severely impaired subjects were generally either very weak (b) or changed with the same proportion across tasks (c), thereby providing very little information for the classification.

Table 1

Mean (SD) classification accuracy (%): Effects of impairment level and number of training sessions

Number of training sessions	Subject impairment level			
	2	**3**	**4**	**5**
2	31.6 (21.5)	43.9 (20.0)	74.2 (15.0)	66.1 (24.8)
3	33.5 (17.3)	42.5 (18.4)	77.2 (12.1)	67.6 (22.2)
Mean	32.6 (19.4)	43.2 (19.2)	75.7 (13.6)	66.9 (23.5)

Table 2

Confusion matrices of the classification results, averaged for two subject groups. Diagonal elements (shaded) denote incidence rates of correct classification, and off-diagonals denote incidence rates of false identification (Units: %).

(a) Highly-impaired								
		Intended Task						
		HO	KG	SG	CG	PG	3G	NM
Classified Task	HO	51.3	22.2	14.7	15.9	17.0	15.9	24.4
	KG	9.5	40.9	10.1	11.7	27.4	16.8	6.3
	SG	3.3	6.9	44.6	27.8	9.0	17.0	0.2
	CG	2.6	5.3	15.2	27.8	8.3	17.2	1.2
	PG	8.2	12.2	5.7	3.7	25.5	8.3	4.7
	3G	3.0	7.3	7.2	11.3	7.6	23.0	1.4
	NM	22.1	5.2	2.4	1.7	5.2	1.8	61.8

(b) Moderately-impaired								
		Intended Task						
		HO	KG	SG	CG	PG	3G	NM
Classified Task	HO	90.8	0.8	1.3	0.5	0.7	0.7	4.8
	KG	0.2	71.7	2.4	2.5	10.8	8.8	0.1
	SG	0.1	3.7	64.6	20.8	2.5	8.8	0.1
	CG	0.0	3.0	25.4	68.3	0.8	14.7	0.7
	PG	2.6	11.2	1.2	1.7	75.0	11.4	0.9
	3G	0.5	9.4	5.2	5.5	8.9	54.8	0.5
	NM	5.8	0.1	0.1	0.8	1.3	0.9	92.9

Table 3

SED matrices of four muscle groups (a: all, b: hand intrinsic muscles, c: forearm anterior muscles, d: forearm posterior muscles) averaged for two subject groups. Diagonal elements (shaded) denote intra-task variability, and off-diagonals denote the inter-task variability.

(a) D: highly-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.65	1.62	1.93	1.76	1.52	1.59	1.27
	KG		0.64	0.93	0.86	0.46	0.67	2.33
	SG			0.66	0.60	0.82	0.77	2.85
	CG				0.67	0.67	0.54	2.59
	PG					0.64	0.60	2.37
	3G						0.67	2.31
	NM							0.41

(b) D: moderately-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.63	2.22	2.18	2.05	2.18	2.23	2.79
	KG		0.67	1.93	1.57	1.02	1.18	3.50
	SG			0.77	0.97	1.90	1.54	3.81
	CG				0.61	1.56	1.17	3.47
	PG					0.68	0.94	3.57
	3G						0.64	3.72
	NM							0.57

(c) D_{HI}: highly-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.46	1.11	1.39	1.24	1.05	1.13	0.72
	KG		0.41	0.53	0.47	0.32	0.47	1.59
	SG			0.46	0.45	0.53	0.52	1.90
	CG				0.45	0.40	0.35	1.69
	PG					0.37	0.43	1.56
	3G						0.50	1.53
	NM							0.21

(d) D_{HI}: moderately-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.42	1.96	1.46	1.44	1.92	1.84	1.72
	KG		0.49	1.47	1.12	0.72	0.77	2.85
	SG			0.53	0.76	1.48	1.25	2.65
	CG				0.35	1.04	0.92	2.39
	PG					0.48	0.57	2.77
	3G						0.42	2.81
	NM							0.26

(e) D_{FA}: highly-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.29	0.69	0.82	0.76	0.67	0.69	0.63
	KG		0.36	0.44	0.37	0.19	0.29	1.08
	SG			0.29	0.22	0.35	0.33	1.30
	CG				0.28	0.27	0.25	1.18

(f) D_{FA}: moderately-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.25	0.60	0.86	0.84	0.67	0.76	1.45
	KG		0.25	0.55	0.45	0.36	0.43	1.39
	SG			0.32	0.31	0.57	0.35	1.71
	CG				0.30	0.60	0.34	1.56

(e) D_{FA}: highly-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
	PG					0.36	0.27	1.14
	3G						0.27	1.08
	NM							0.25

(f) D_{FA}: moderately-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
	PG					0.30	0.41	1.50
	3G						0.27	1.60
	NM							0.31

(g) D_{FP}: highly-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.23	0.78	0.94	0.87	0.74	0.78	0.72
	KG		0.24	0.57	0.57	0.24	0.35	1.15
	SG			0.32	0.29	0.47	0.41	1.51
	CG				0.34	0.40	0.29	1.37
	PG					0.29	0.25	1.21
	3G						0.29	1.21
	NM							0.20

(h) D_{FP}: moderately-impaired

		Task						
		HO	**KG**	**SG**	**CG**	**PG**	**3G**	**NM**
Task	HO	0.31	0.67	1.09	1.03	0.58	0.82	1.54
	KG		0.30	1.01	0.82	0.45	0.61	1.36
	SG			0.37	0.45	0.94	0.70	2.00
	CG				0.34	0.82	0.51	1.87
	PG					0.33	0.54	1.53
	3G						0.35	1.70
	NM							0.32

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