On Muscle Activation for Improving Robotic Rehabilitation after Spinal Cord Injury

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***Abstract*— Spinal cord stimulation (SCS) has recently enabled humans with motor complete spinal cord injury (SCI) to independently stand and recover some lost autonomic function. However, the nature of the recovered motor activity and the interplay between SCS and motor training are not well understood. Understanding the effect of stand training and spinal stimulation on motor activity during bipedal standing is important for designing spinal rehabilitation therapies that seek to combine spinal stimulation and rehabilitative robots. In this study, we examined electromyography (EMG) data gathered from two SCI patients and six healthy subjects as they attempted standing. We analyzed the muscle activation patterns and EMG waveform shape to quantify both the changes in SCI patient motor activity with training, and the differences between healthy motor activity and SCI patient motor activity under stimulation. We also looked for correlations between the similarity in SCI patients' motor activity to healthy subjects and their overall standing ability. We found that good standing in SCI patients does *not* emulate healthy standing muscle activity. Furthermore, patient stand training heavily influenced motor activation patterns, but not in ways that improved standing ability. These results indicate that current training techniques do not optimally influence motor activity, and robotic rehabilitation strategies for SCI patients should target essential features of motor activity to optimize functional performance, rather than emulate healthy activity.**

I. INTRODUCTION

Spinal Cord Injury (SCI) is a debilitating condition that afflicts ∼350,000 people in the U.S., and 5 million worldwide. Complete SCI leads to full paralysis, with no voluntary motor control, below the level of the injury. However, electrical spinal stimulation, using multi-electrode arrays implanted over the lumbosacral spinal cord (see Fig. 1), has enabled *complete*, paralyzed SCI patients to achieve independent weight bearing standing, some weight-assisted stepping, and partial recovery of lost autonomic function [1], [2]. Preliminary studies have shown that proper physical therapy should be combined with spinal stimulation to achieve better recovery [3]. Surface electromyographic (EMG) recordings obtained during therapy sessions play a valuable role in understanding patient progress under spinal stimulation, and recent results have shown that SCI patient standing ability can be accurately predicted based on EMG features [4]. However, little is known about the effects of robotic training on the EMG activity of complete SCI patients under spinal stimulation. A better physiological understanding of these effects can offer guidance on the design of rehabilitation robots by informing us on optimal ways to guide EMG activity.

This paper presents the first study analyzing the effect of stand training on EMG activity of complete SCI patients, and comparing EMG signals in spinally stimulated SCI patients with those of healthy subjects. An understanding of their differences as well as the factors that do and do not contribute to good standing in SCI patients will allow us to better design spinal stimulation in conjunction with robotic rehabilitation. It has been shown that EMG signals can be used with machine learning algorithms to automatically optimize multi-electrode array stimulation parameters in animals with SCI [5]. Quantification of EMG signal changes due to electrical stimulation and stand training could similarly inform rehabilitative strategies for robotic devices (e.g. Lokomat trainer or exoskeletons) which are coupled with spinal stimulation. Recent experiments [6] show that the combination of stimulation with robotic rehabilitation devices leads to synergistic outcomes.

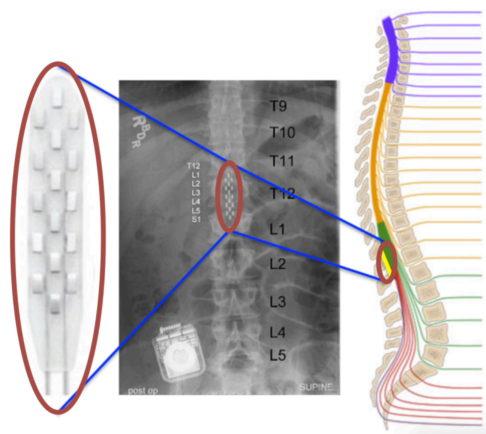

Fig. 1: Spinal cord stimulation with 16-electrode array implantation. The array applies a specific pattern of electrical stimulation to the spinal cord.

As a motivation of this work, we are developing a perturbation platform to train (and test) SCI patient motor function under spinal stimulation, shown in Figure 2. The platform is able to tilt in any direction at high rotational speeds, as well as translate up and down. This type of robotic trainer will allow us to modulate the pattern of muscles that are activated through the tilt angle, and also influence the sensorimotor pathways that are activated by modifying the rotational speed (e.g. high speed tilts will activate reflexive pathways).

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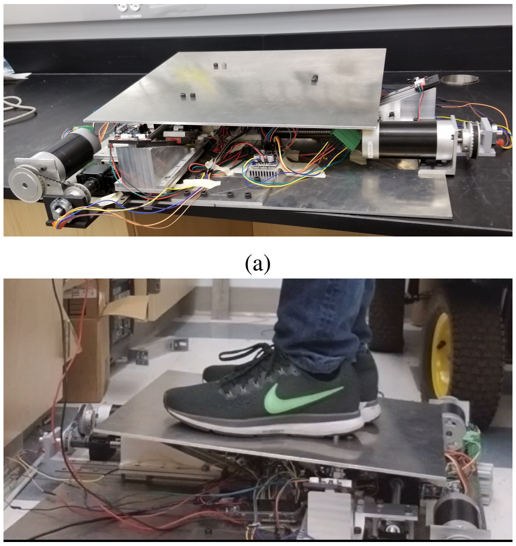


(a)

(b)

Fig. 2: (a) Perturbation platform for patient training, which can tilt in any direction (roll/pitch) and translate up/down; (b) Subject standing on the platform at a given tilt angle.

However, the theory on how muscle activity changes under spinal stimulation and with motor training is unknown, and so optimal rehabilitation strategies are unknown. Studies have examined the effects of robotic training and therapist training on patients with SCI, noting their importance in improving muscle activity [7]–[10]. Many current strategies center around training patients to emulate healthy subject activity [3], [11], [12]. However, the muscle activity in spinally stimulated standing is markedly different from that of healthy human subjects during quiet standing. Compared to healthy standing, balance is more difficult to achieve and standing is mainly controlled by spinal circuits activated via the stimulating electrode array, rather than via the patient's voluntary motor control system [1], [2], [13]. This suggests that SCI patients may be subject to different constraints in neural activity, resulting in different solutions for muscle activation when trying to achieve the same goal.

Therefore, we hypothesize that the effects of training on EMG in SCI patients under spinal stimulation may be markedly different from the changes seen in neurologically intact subjects. This paper seeks to further our understanding of the effects of motor training in spinally stimulated SCI patients (and their relation to healthy human subjects) with the goal of designing robotic rehabilitation devices and strategies for optimal motor recovery after SCI. For example, if certain muscle co-activation patterns are identified to be important, we could design our robotic platform to apply perturbations that excite corresponding sensorimotor pathways.

To gain this understanding, we examine the features of SCI patients' EMG activity during standing (both before and after a six month period of stand-training or no-stand-training), and see how they change, as well as how they compare to EMG features of several healthy subjects. The three main findings of this work are that:

- EMG activity for good standing in SCI patients under spinal stimulation does *not* emulate EMG activity in healthy subjects,
- Stand training can induce significant changes in EMG activity, greater than changes from stimulation alone,
- Changes in EMG activation induced by stand training do not target features most important to standing performance improvement, indicating the need for modified training strategies with spinal stimulation.

These findings challenge the current wisdom on robotic rehabilitation strategies that aim to emulate healthy human muscle activity, and inform us on what features of the muscle activity we should target through rehabilitative robots that are not being effectively trained.

II. METHOD

A. Human Experiments

1) Standing Musculoskeletal Model: Fig. 3 shows a simple musculoskeletal model of the human leg muscles studied in this work (generated in OpenSim [14]). It depicts the locations of these muscles and the joints they actuate. The knee joint is extended by the vastus lateralis (VL) and flexed by medial hamstring (MH). The medial gastrocnemius (MG) and the soleus (SOL) generate dorsiflexion and plantarflexion (pull and push) torques at the ankle, respectively. For control of standing, solutions are not unique as many combinations of subgroup muscle activation can maintain stable posture.

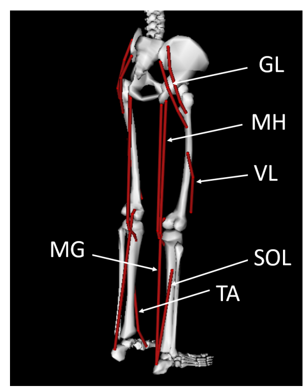


Fig. 3: Musculo-skeletal model of human leg muscles studied.

2) SCI Patient Experiments: Data was collected from two complete, paraplegic SCI patients, referred to as patients ATC and ARI, implanted with a Medtronic 5-6-5 epidural electrode array for spinal cord stimulation with a Medtronic RestoreAdvanced Neurostimulator. The injury was in the high thoracic spinal cord for both patients. Experiments were performed over two non-consecutive weeks, six months apart, allowing us to observe home stand training effects.

For each measurement trial, spinal stimulation began while the patient was seated. Then the participant initiated the sit to stand transition by positioning his feet shoulder width apart and shifting his weight forward to begin loading the legs. As shown in Fig. 4, the participant used the horizontal bars of the standing apparatus during the transition phase to balance and to partially pull himself into a standing position. The patient then attempted to stand with minimal support for ≈ 5 minutes under spinal stimulation. Note that spinal cord stimulation induces the resulting muscle activity of the patient by modulating the patient's spinal circuits, which is different from functional electrical stimulation in which the stimulation directly stimulates the patient's muscle activity.

Fig. 4: Image of SCI patient attempting to stand under spinal stimulation. A stand frame wraps around the patient for safety and support (if needed), and clinicians sit in front of and behind the patient for support (if needed).

The choice of stimulating electrodes recruited on the array and their polarities were modified between trials. This choice was determined by a machine learning algorithm which continually proposed different "safe" stimuli (high probability of eliciting non-painful response), and continually tested good ones against each other to search for the optimal stimulation patterns (resulting in independent, natural standing) [15], [16]. Stimulation frequency and pulse width were kept constant between trials at 25 Hz and 200 μs, respectively. For a given stimulation pattern, frequency, and pulse width, SCS amplitude was ramped upward until reaching a well-performing value. The patient achieved full weight-bearing standing with minimal assistance when empirically-optimal stimulating configurations were used.

We utilized measurements from 8 muscles (left and right muscles of 4 muscle groups) taken using surface EMG at a sampling frequency of 2000 Hz. The 4 muscle groups were: VL (Vastus Lateralis), MH (medial hamstring), MG (medial gastrocnemius), and SOL (soleus). These are shown in Figure 3. The EMG was low-pass filtered at 200 Hz, and then high-pass filtered at 1 Hz using a 5th order butterworth filter.

Table I describes how the clinicians quantified standing quality. We utilized a discrete scoring system that ranges from 1 to 10. From scores 1 to 5, the standing is not independent but requires less and less assistance by bungees or trainers as the score increases. From scores 6 to 10, standing is overall independent and full-weight bearing. As the score increases, standing is more natural, stable, and durable. After every trial, a score on the overall standing quality was assigned. The range of realized scores was $[3.25, 8.75]$ for patient ARI and $[1.25, 10]$ for patient ATC.

Both patients received rigorous stand training in the clinic prior to the first measurement session. Stand training in this study involved the use of a rigid frame to practice quiet standing under spinal stimulation. In the six months between sessions, patient ATC continued stand training at home utilizing a stand frame similar to the one shown in Figure 4. Patient ARI was unable to do stand training in the six months between his first and second session. Thus we can compare patients ATC and ARI to analyze the differences of having stand training over a six month period versus not training over a six month period.

TABLE I: The Scoring Criterions

Score	Descriptions
1-2	Assisted by bungees or trainers (max)
3-4	Assisted by bungees or trainers (mod)
5	Assisted by bungees or trainers (min)
6-7	Hip: Not assisted, back arched Knee: Not assisted, loss of extension during shifting
8-10	Hip: Not assisted, back straight Knee: Not assisted, extended during shifting

3) Healthy Patient Experiments: Data was collected from six healthy participants (age: 27.2 $\pm$ 4.5 years; height: 168 $\pm$ 9 cm; weight: 62.3 $\pm$ 10.9 kg). They had no medical history of neurological disorders. Each participant stood quietly with bare feet, eyes open, and arms hanging along the sides of the body for the duration of 60s. The participant was instructed to stand quietly and refrain from voluntary movements.

Surface electromyograms (EMGs) were recorded from the same muscles measured bilaterally in the participants with SCI (VL, MH, MG, SOL). EMG signals were differentially amplified with a band-pass filter with a bandwidth between 10 and 2,000 Hz (-3 dB), and digitized at a sampling frequency of 4000 Hz. To compare results with the SCI patients, we downsampled the signal to emulate a sampling frequency of 2000 Hz. The EMG was then low-pass filtered at 200 Hz and then high-pass filtered at 1 Hz using a 5th order butterworth filter, as was done for the SCI patients.

Therefore, both patients followed the same experimental protocol for quiet standing with the same muscles examined and similar EMG filtering (though the healthy subject EMG was preprocessed with 10-2000Hz bandwidth during data collection). The main procedural difference was that the SCI patients needed support from therapists and a stand frame in many quiet standing trials, whereas the healthy subjects needed no support.

B. EMG Feature Selection and Extraction

Traditional methods such as time-domain and frequency-domain analyses have been widely utilized in EMG pattern recognition [17], and they are capable of tracking muscular changes. Other methods like Bayesian estimation [18] and linear filtering also achieve good estimates of muscle forces. Recently, [4] showed that a 4^{th} order Auto-Regressive(AR) model on each EMG channel could very accurately predict SCI patient standing ability under spinal stimulation.

In this study, we want to utilize quantitative features of the patients' EMG activity that capture physiologically meaningful characteristics of the EMG activity. By using physiologically meaningful features, we can gain interpretable insight into our patients' changes in motor activity, rather than focus exclusively on prediction of functional outcomes. Work on muscle synergies in the neuroscience community [19]–[22] supports the idea that motor activity in both healthy subjects and SCI patients can be reasonably approximated by an encoding of (1) the relative muscle activation pattern, and (2) the EMG signal waveform. The theory is that EMG *signal waveforms* are derived from neural commands sent by the central nervous system, which activate neural networks in the spinal cord that results in a relative *muscle activation pattern*. Therefore, features that describe the relative muscle activation pattern and the EMG signal waveform give us reasonable insight into the rehabilitative processes that occur at these two levels.

To describe the muscle activation pattern, we extract the relative EMG activation power of different muscles as a quantitative feature. For each trial, we take the EMG power of each channel, and then normalize by the L_2 norm of the EMG power from all channels. This feature, which we define as the activation pattern, W, describes the *relative* activation power of the 8 different muscles (discounting their absolute activation power), and is represented by a vector in $\mathbb{R}^8$.

To describe the EMG signal waveform, a 10^{th} order Auto-Regressive(AR) model was fit to each EMG channel, leading to ten extracted coefficients for each EMG signal. For 8 channels (one for each muscle), a total of 80 features were extracted per observation. We then applied principal component analysis to the AR model features to reduce the feature set to the top 8 dimensions, which capture greater than 99.8% of the variance ($>$ 99.8% variance accounted for). This allows for features of the same dimension ($\mathbb{R}^8$) to be used to describe the EMG activation pattern and EMG waveform. The AR model is invariant to the EMG absolute amplitude, and the resulting features capture the EMG waveform *shape* for each channel.

Therefore, we are able to separately describe the relative muscle activation pattern and EMG waveform shape through the W features and AR model features, respectively.

Note that we cannot utilize EMG power as an accurate metric, as the absolute amplitude of the EMG varies substantially between experimental groups due to different EMG electrode type, application methods, and amplification. Therefore, we utilize features that are invariant to the EMG absolute amplitude.

III. Results and Analysis

We want to answer the following main questions:

- What features of EMG activity are most important to good standing performance in SCI patients under spinal stimulation, and how does stand training influence these features? This insight will allow us to evaluate the efficacy of the current training strategy, and identify important areas for robotic trainers to focus on.
- How does stand training in spinally stimulated SCI patients influence the similarity of their EMG activity to heathy subjects' EMG activity, and does similarity to healthy activity correlate with improved standing ability? This insight could inform whether we should design training strategies around emulating the behavior of healthy subjects, or consider training different behaviors that focus on the same functional outcome (e.g. good standing).

Subsection (A) sets the stage by noting the high degree of separability between different patients and different sessions, and visualizing this separability. Subsections (B) and (C.1) answer the first question by studying how EMG features change with stand training and spinal stimulation versus spinal stimulation alone, and analyzing correlations of those EMG features with the patients' standing scores. Subsections (C.2) and (C.3) answer the second question by examining the similarity of healthy subjects' EMG activity to the SCI patients' EMG activity, and finding correlation between that similarity and the patients' standing ability.

A. Comparison of Healthy vs. SCI EMG Activation

To compare healthy EMG activity with SCI EMG activity, we compared their AR model features and W features to quantify the differences between the EMG waveform and activation pattern, respectively. Figure 5 visualizes these differences by projecting the AR model features and W features onto their top 3 principal components and plotting the result. Each point represents the EMG activity for a single patient trial.

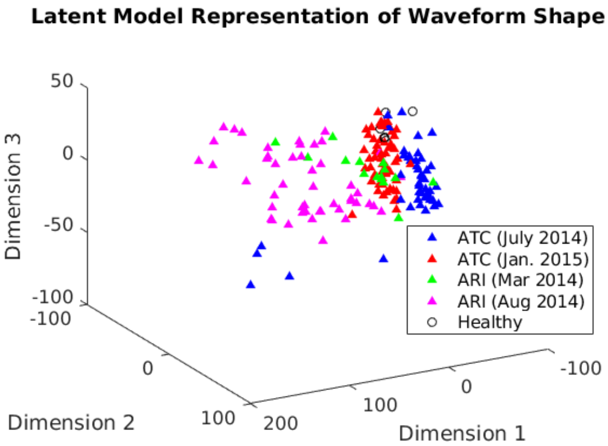
From Figure 5, we note that even with only 3 principal components, there is reasonable separation in the EMG waveform shape between each patient and the healthy subjects, and between the two sessions of each patient. For the EMG activation pattern W, there is also clear separation between healthy subjects and the SCI patients, although there is significant variability in the activation pattern of patient ARI's second session.

To quantify these findings, we train a linear support vector machine (SVM) using the EMG waveform shape features (AR model) and find that we get 97% classification accuracy with all healthy subjects accurately classified. When using the activation pattern features, W, the linear SVM achieves 95% classification accuracy with one of the healthy subjects misclassified as an SCI patient. Note we are currently only checking for linear separability of the data, rather than predictability.

B. Influence of EMG activation pattern and waveform on standing ability

First, we look at the muscle activation pattern features, W, to see if they are highly correlated with patient score. If they are, this would be an indicator that good muscle activation patterns are important to good standing.

We train multi-class SVMs with either a linear or RBF kernel, and optimize their hyperparameters in order to predict the patient's standing scores. We use W as the features, and utilize 3-fold cross-validation to test our results. The results for our 5-class SVM are summarized in the confusion matrix in Figure 6a, and show that the W features perform very poorly at predicting patient standing ability. With the 5 classes shown, we get an overall classification accuracy



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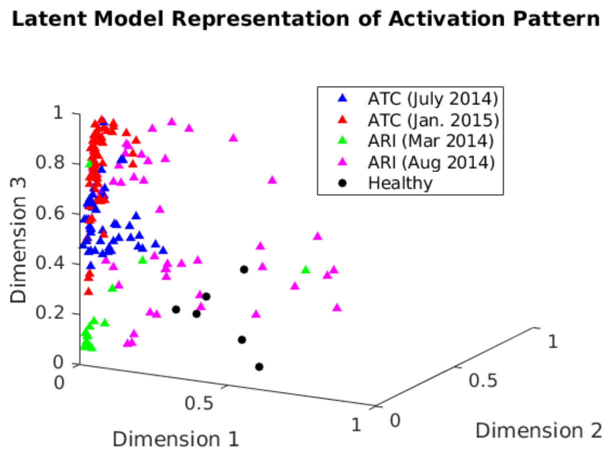


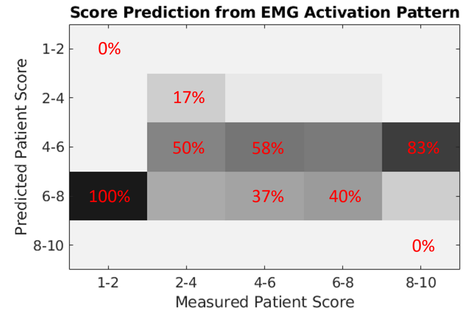
(b)

Fig. 5: (a) Visualization of differences in EMG waveform shape between the different subjects and across different sessions. Visualized by projecting AR model coefficients onto the top 3 principal components; (b) Visualization of differences in muscle activation pattern between the different subjects and across different sessions. Visualized by projecting W onto the top 3 principal components.

of 35%, and two classes are completely miscategorized. In contrast, Figure 6b taken from [4] shows that AR model features exhibit very high correlation with standing score.

Comparing Figures 6a and 6b, we note that using AR model features (waveform shape), the standing score can be predicted to the nearest integer (on a scale from 1-10) with an overall prediction accuracy of 93%; Using W features (activation pattern), the standing score is poorly predicted with an overall prediction accuracy of 20% when trying to predict to the nearest integer. Although the poor prediction accuracy using W is likely exacerbated by the non-uniform distribution of scores in the dataset, the fact that the AR model achieved very high accuracy with patient ATC indicates that the muscle activation pattern W is much less influential in patient standing ability.

These preliminary results suggest that good rehabilitation strategies should aim to influence patients' EMG waveform shape rather than the activation pattern (this challenge is considered in the Discussion section).



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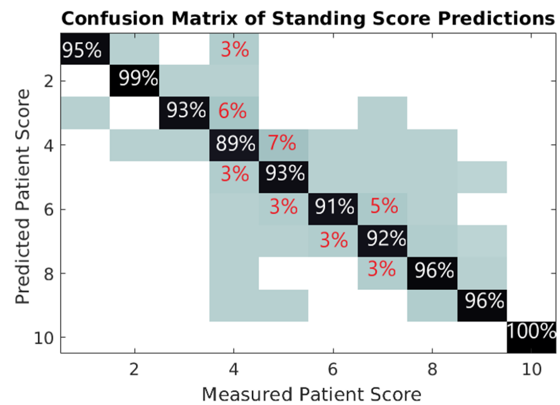

(b)

Fig. 6: (a) Accuracy in standing score prediction using 5-class SVM with W features (muscle activation pattern); (b) Accuracy in standing score prediction for patient ATC using 10-class SVM with AR model features (EMG waveform shape). Results taken from [4].

C. *Effects of Stand Training on EMG Activity*

1) Effects of Stand Training versus Spinal Stimulation: After comparing the importance of different features to standing, we would like to see how stand training influences the EMG features. We can calculate the change in the EMG waveform and activation pattern between sessions in order to approximate the effect of time/training. Using the visualization in Figure 5, we can consider each trial as a point in the EMG feature space, and each session is represented by a cluster of points (red, blue, green, or purple).

To calculate the change in EMG features between sessions (C^W_{train} and C^{AR}_{train} in Equation 1), we take the L_2 distance from each point (i.e. trial) in one cluster (corresponding to one session) in the EMG feature space to the centroid of the other cluster (corresponding to the other session) in the same space. This metric is defined in Equation 1, which gives us a distribution on the change in EMG activity after six months.

We also approximate the magnitude of the effect of spinal stimulation (C^W_{stim} and C^{AR}_{stim} in Equation 2) by calculating the variance of the distance from each trial (i.e. point) within a session from the mean features (i.e. cluster centroid). This metric, defined in Equation 2, gives us a distribution on the variation in EMG activity between trials of the same session where different spinal stimulation patterns were used. Thus we have a measure for the magnitude effect of spinal stimulation (based on the intra-cluster variation) as well as a measure for the magnitude effect of time/training (based on inter-cluster distances).

$$C^{W}_{train}(i) = ||W_{S2}(i) - \overline{W}_{S1}||_2$$
$$C^{AR}_{train}(i) = ||AR^{proj}_{S2}(i) - \overline{AR}^{proj}_{S1}||_2\ ,\quad i = 1, ..., N \tag{1}$$

$$C^{W}_{stim}(j) = ||W_{S1}(j) - \overline{W}_{S1}||_2$$
$$C^{AR}_{stim}(j) = ||AR^{proj}_{S1}(j) - \overline{AR}^{proj}_{S1}||_2\ ,\quad j = 1, ..., M \tag{2}$$

Here W_{Sk} represents the activation pattern features for session k , AR^{proj}_{Sk} denotes the AR model features projected onto the top 8 principal components for session k, the indices i, j index the i^{th} trial of session 2 or the j^{th} trial of session 1, and $\bar{W}$, $\bar{AR}^{proj}$ denote the mean activation pattern and mean AR model feature, respectively.

We use these measures to determine how, or whether, training/time (i.e. the 6-month inter-session period) have an effect on the patient's EMG activity. Recall that patient ATC received stand training during the inter-session period, while patient ARI did not. If the intercluster distances are statistically significantly *greater* than the intracluster variation (effect of spinal stimulation), then we can conclude that the patient's training is affecting the EMG activity in a way which is not due to spinal stimulation alone. However, if the intercluster distance is approximately equal to or less than the intracluster variation, then what seems to be the effect of patient training/time may be due to variations from spinal stimulation.

Figure 7 shows the approximation of the effect of spinal stimulation vs. the effect of training/time on the patients' EMG activation pattern and waveform shape. We note that the EMG activation pattern for patient ATC is significantly affected by training – change from training is much greater than the variation from spinal stimulation – and a significant effect also is seen on the activation pattern for patient ARI. However, there is no discernible effect of training/time on the EMG waveform shape for either patient.

To confirm this qualitative observation, we utilize the two-sample t-test to determine if the effect of training is statistically significantly greater than the variation from spinal stimulation. We want to *reject* the null hypothesis that the distribution of EMG activity after training is consistent with the original distribution prior to training.

We find that the activation pattern, W, changes at a 1% significance level for both patients ATC and ARI (p-value = $1.07e-22$ for ATC, p-value = $5.9e-7$ for ARI). We hypothesize that both training and the absence of training influence activation pattern – patient ATC followed a home stand training schedule which was different from the stand training done in the clinic, and patient ARI was unable to do stand training during that time. Thus patient activity (manner of training or the absence of training) influences the muscle activation pattern that SCI patients utilize under SCS.

There was no statistically significant change in the EMG waveform shape between the two sessions for either patient,

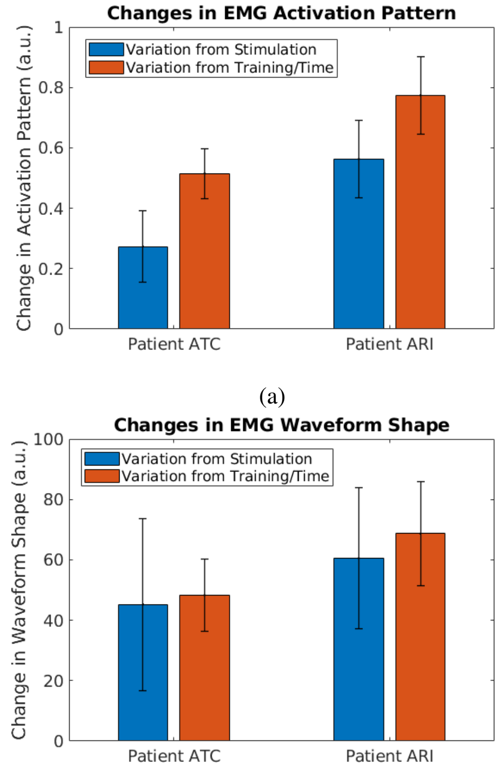

Fig. 7: (a) Change in activation pattern from intra-session variation due to spinal stimulation, compared with inter-session change (pre- and post-six month period); (b) Change in EMG waveform shape from intra-session variation due to spinal stimulation, compared with inter-session change (pre- and post-six month period).

even at the 20% significance level (p-value = 0.46 for ATC, p-value = 0.22 for ARI). Thus while stand training can have an effect on SCI patients' muscle activation pattern, we cannot conclude that stand training has any influence on the EMG waveform shape (which we saw in Section III-B is the feature that is highly correlated with patient standing ability). Note that this does *not* mean that training does not affect the EMG waveform shape, but only that the effect is not large enough for our analysis to separate it out from the effect of spinal stimulation.

2) Effect of Training on Similarity to Healthy EMG: Given the statistically significant shift in activation pattern, we want to examine whether time and training push the patient closer to the EMG behavior of healthy subjects. We define a metric for the distance from healthy standing as the minimum L_2 norm from each trial in feature space to the closest healthy subject trial in the same space. This is represented in Equation 3.

$$D^{W}_{Sk}(i) = min_{j\in H}||W_{Sk}(i) - W_{healthy}(j)||_2$$
$$D^{AR}_{Sk}(i) = min_{j\in H}||AR^{proj}_{Sk}(i) - AR^{proj}_{healthy}(j)||_2 \tag{3}$$
$$i = 1, ..., N_k$$

The notation is the same as in Equations 1 and 2 with the addition that H represents the set of healthy subjects, and

N_k is the number of trials in session Sk.

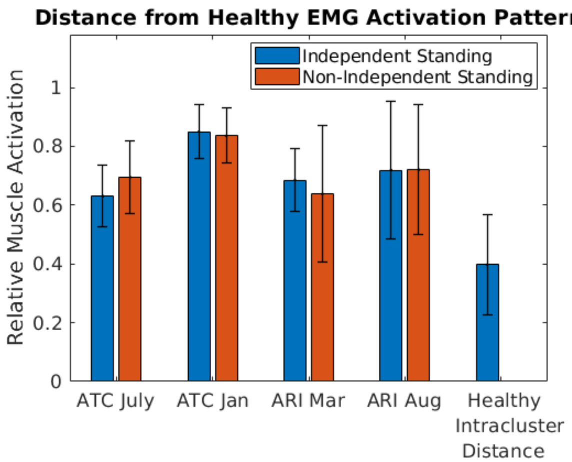

Fig. 8: Distance from healthy muscle activation pattern for each patient both before and after six month period. Results divided between trials of non-independent standing (score < 6) and independent standing (score ≥ 6).

We only examine the training effect on the EMG activation pattern for patients ATC and ARI, since we saw from Section III-C.1 that the training effect on EMG waveform shape was *not* significantly greater than the effect of spinal stimulation.

Figure 8 shows the distance from healthy subjects' EMG activation pattern both before and after the six month home period. First, we confirm that there is a statistically significant difference in the EMG activation pattern for SCI patients vs healthy subjects (i.e. the intercluster distance between the features of healthy subjects and SCI patients is greater than the intracluster variation between the healthy subjects). This difference is statistically significant at the 0.1% significance level for both patients/sessions.

Then we note that patient ATC's distance from healthy subjects' EMG activation pattern actually *increases* after stand training. In contrast, such a conclusion about patient ARI's distance from healthy subjects' EMG activation pattern cannot be made due to the higher variances. In order to quantify the statistical significance of these differences, we utilize the two-sample t-test in order to reject our null hypothesis that the EMG activity before and after the six months are a similar distance from healthy subjects' EMG activity. We find that for patient ATC, there is a statistically significant *increase* in the difference from healthy EMG activation pattern for both cases of independent standing and non-independent standing (with p-values of $1.1e-10$ and $1.1e-5$, respectively) at the 1% significance level.

However, we found that for patient ARI, the difference from healthy EMG activation pattern for the cases of independent and non-independent standing were *not* statistically significant at the 1% significance level (with p-values of 0.63 and 0.55, respectively). Since patient ARI did *not* do stand training at home whereas patient ATC did, we hypothesize that the consistent stand training under spinal stimulation actually pushed the activation pattern *further* from the muscle activation patterns of healthy patients. For patient ATC, this could be a consequence of the stand training at home being significantly different from the standing training done at the clinic (which closely emulated healthy standing). This is supported by the fact that patient ATC's muscle activation patterns drifted further from the healthy ones.

3) Correlation of Score with Similarity to Healthy Standing: We also must ask whether the patient's similarity to healthy standing influences their standing performance. We utilize the metric defined in Equation 3 to measure similarity to healthy standing. Figure 9 shows the patient's standing score versus the distance of the EMG waveform shape from healthy subjects' EMG waveform shape (via the AR model features projected on the top 8 principal components). We immediately note that there is no linear correlation linking the two, with linear regression to the data having $r^2 = 0.0044$. To confirm the lack of meaningful correlation, we trained SVMs with either a linear kernel or RBF kernel with optimized hyperparameters, and tested their 3-fold cross-validated performance in classifying non-independent (score < 6) vs. independent standing (score ≥ 6). The highest accuracy we achieve is 50% classification accuracy (comparable to random guessing) and this drops as we introduce more classes for prediction of standing scores.

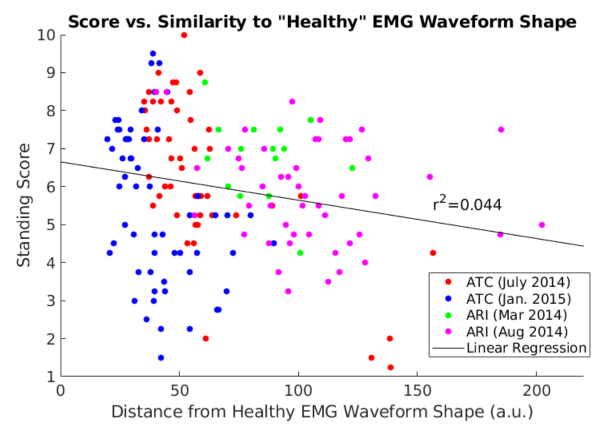

Fig. 9: A scatter plot of patient score versus the distance from healthy EMG waveform (as defined in Equation 3). Each point represents a single patient trial.

The same result was found when considering the distance of the SCI patients' EMG activation pattern, W, from healthy subjects' EMG activation pattern. Linear regression to the data gives $r^2 = 0.049$ and our best-tuned SVMs give 3-fold cross-validated classification accuracy of 55% for classifying independent vs. non-independent standing.

Based on these results, we conclude that the SCI patients' standing performance is not explicitly linked to the similarity of their EMG activity to healthy subject EMG activity. In other words, SCI patients optimize standing performance through a strategy that is distinct from healthy subject behavior and do *not* emulate healthy patient activity.

IV. Discussion

We have seen that current training strategies for SCI patients under spinal stimulation influence EMG muscle activation pattern, but not necessarily the EMG waveform shape – even though the latter has been show to be more critical to good standing under spinal stimulation. This indicates a significant gap between current training strategies and optimal ones, as we are currently not targeting aspects of the EMG activity that are best correlated with functional performance. Therefore, robotic rehabilitation devices should adopt different strategies to train spinally stimulated SCI patients with the aim of modifying their EMG waveform shape. The goal is to have robotic training and spinal stimulation working synergistically to optimize the patient's muscle activity.

Furthermore, we have found that good standing for SCI patients does *not* emulate healthy subject standing, in either muscle activation pattern or waveform shape. This preliminary result suggests that robotic rehabilitation devices should aim to optimize performance-based metrics, rather than attempt to replicate healthy subject motion. In future work, we would like to repeat these analyses with a larger pool of patients, in order to make stronger generalizations about our results to the entire SCI population. However, these preliminary results suggest that current training strategies are suboptimal and warrant a revisiting of robotic rehabilitation devices that seek to emulate healthy subject motion.

With respect to the perturbation platform described in the Introduction, as well as other robotic training devices such as exoskeletons, we should utilize these robotic devices to encourage modification to EMG waveform shape and de-emphasize the importance of the muscle activation patterns that are elicited. However, while the EMG waveform shape is critical, it is very difficult to directly modulate compared to the EMG activation pattern. As seen in this study, patient training did not significantly influence EMG waveform shape. Recent results though have been able to identify muscle synergies (described in Section II-B) in SCI patients and suggest that patient EMG waveform shape can be directly modulated through activation of different muscle synergies [22]. Drawing on this understanding of the central nervous system, we may be able to design more intelligent robotic platforms that work with spinal stimulation to effectively and repeatably target sensorimotor pathways corresponding to important muscle synergies.

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