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RESEARCH ARTICLE

Decoding upper limb residual muscle activity in severe chronic stroke

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Abstract

Objective: Stroke is a leading cause of long-term motor disability. Stroke patients with severe hand weakness do not profit from rehabilitative treatments. Recently, brain-controlled robotics and sequential functional electrical stimulation allowed some improvement. However, for such therapies to succeed, it is required to decode patients' intentions for different arm movements. Here, we evaluated whether residual muscle activity could be used to predict movements from paralyzed joints in severely impaired chronic stroke patients. **Methods**: Muscle activity was recorded with surface-electromyography (EMG) in 41 patients, with severe hand weakness (Fugl-Meyer Assessment [FMA] hand subscores of 2.93 ± 2.7), in order to decode their intention to perform six different motions of the affected arm, required for voluntary muscle activity and to control neuroprostheses. Decoding of paretic and nonparetic muscle activity was performed using a feed-forward neural network classifier. The contribution of each muscle to the intended movement was determined. **Results**: Decoding of up to six arm movements was accurate (>65%) in more than 97% of nonparetic and 46% of paretic muscles. **Interpretation**: These results demonstrate that some level of neuronal innervation to the paretic muscle remains preserved and can be used to implement neurorehabilitative treatments in 46% of patients with severe paralysis and extensive cortical and/or subcortical lesions. Such decoding may allow these patients for the first time after stroke to control different motions of arm prostheses through muscle-triggered rehabilitative treatments.

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Introduction

Stroke is one of the main causes of long-term motor disability worldwide and in more than 85% result in functional deficits in motor control.[1] Currently, about 75% of patients affected by a stroke survive 1 year or more and this proportion will increase in the coming years due to improving quality of care. Furthermore, of stroke survivors showing no active upper limb motion at hospital admission, ~14% recover completely, 30% partially and 56% show little or no recovery.[2] The holistic, comprehensive, interactive approach of an interdisciplinary team is the hallmark of stroke rehabilitation.[3] For motor recovery in the chronic phase of stroke rehabilitation intensive motor therapy interventions are necessary. To promote the effects of physical therapy researchers and clinicians suggest intensive exercise and augmented feedback,[4] Constraint Induced Movement Therapy (CIMT),[5] exercise in virtual environments with feedback to assist skill learning.[6] However, it has been estimated that only 20% to 25% of stroke patients have wrist or finger movements needed for CIMT.[7] Chronic stroke survivors with severe hand weakness show limited residual muscle activity in the upper arm extensor muscles and no residual finger extension. Currently, there is no accepted and efficient rehabilitation strategy available, with the exception of brain machine interfaces.[8]

Dysfunction in a muscle involved in a movement results in an abnormal synergistic muscle pattern.[9] Sadly, such dysfunction leads to a reduction in muscle use (learned nonuse) and muscle atrophy. These factors add to spasticity and weakness resulting in impaired affected upper and lower extremity use. In order to overcome the absence of appropriate control of paretic muscles in stroke patients new rehabilitation therapies based on the combination of robotics and brain control of upper limb assistive technology[10–13] have been proposed showing to improve neurorehabilitation.[8,14–20] One problem of this approach is that the accuracy to detect intention or movement by noninvasive brain signals is limited.[21–24] On the other hand, surface electromyography (sEMG) activity has been successfully used for the accurate decoding of many dexterous movements[25–29] for prosthesis' control, making it an attractive tool as a source of control for motor restoration robotics or orthotics.

In this study, we aim at characterizing the feasibility to decode residual EMG activity recorded by sEMG when 41 chronic stroke patients defined as severely paretic attempt seven different forearm and upper arm movements, a required first step to allow successful use of these signals as controllers of multimotion mechanical orthosis for rehabilitation.

Patients and Methods

Subject recruitment

Forty-eight right-handed and six left-handed chronic stroke patients with no active finger extension, Fugl–Meyer Assessment (FMA) hand scores of 2.5 ± 1.5 (max score 24 points) and age 55.01 ± 11.3 years, were recruited[8] (see Table 1). From the 48 patients, seven patients had to be excluded from the final analysis for technical reasons (poor signal to noise ratio; $N = 2$) and insufficient trials left after artifact removal ($N = 5$) (see Data S1 for an extensive explanation of the exclusion criteria). A modified version of the upper limb FMA was performed 1 day before the EMG recording[30] (for extended explanation see Data S1). A summary of patient groups demographic and functional data are presented in Table 1.

Written informed consent was obtained from all patients. The study was approved by the ethics committee of the Faculty of Medicine of the University of Tübingen (Germany).

Experimental design

The patients were placed on a comfortable chair while different auditory and visual cues were presented corresponding to six different forearm and upper arm movements: (1) shoulder flexion, (2) external rotation of the shoulder, (3) upper limb supination, (4) extension of the elbow, (5) wrist extension and (6) finger extension (Fig. 1C). These movements were selected because of their relation with the upper limb motor skilled movements used in the FMA scale.

An instruction of 3 sec was shown with three pictures of the movement to perform (beginning, half and end of movement) (Fig. 1C). Subsequently, two "Ready" and one final "GO" cue were presented for 1 sec each. After the "GO" cue, the patients had 6 sec to perform the movement, reach the final position and maintain posture before a "Relax" cue was presented. During each movement, the patients were presented with a classical music piece (different for each movement) increasing in volume throughout the entire 12 sec of each trial (instructions + ready + movement) (see Fig. 1B). This was used as a rhythmic-melodic motivational tool. A silent intertrial

Table 1. Group demographic and functional data.

No.	Age	Handiness	Affected limb	Lesion location	Months since stroke	FMA hand/24	FMA arm/30	cFMA/54
48	55.01 ± 11.3	42R/6L	15R/33L	21 cort-sub 27 sub	72.3 ± 56.2	2.5 ± 1.5	8.53 ± 5.9	11.04 ± 6.6

FMA, Fugl–Meyer Assessment; cFMA, combination FMA.
Number of participants, mean and standard deviation of age, handedness, affected arm, lesion location, mean and standard deviation of months since stroke and hand, arm and a combination hand and arm of the Fugl–Meyer upper limb motor scores. R and L stand for right and left, respectively. Cort stands for cortical and sub stands for subcortical stroke. cFMA stands for the motor part of the modified upper limb Fugl Meyer Assessment (cFMA) (Hand and arm parts combined having a maximum score of 54 points). Coordination speed and reflexes were not included because of the severity of the paralysis.

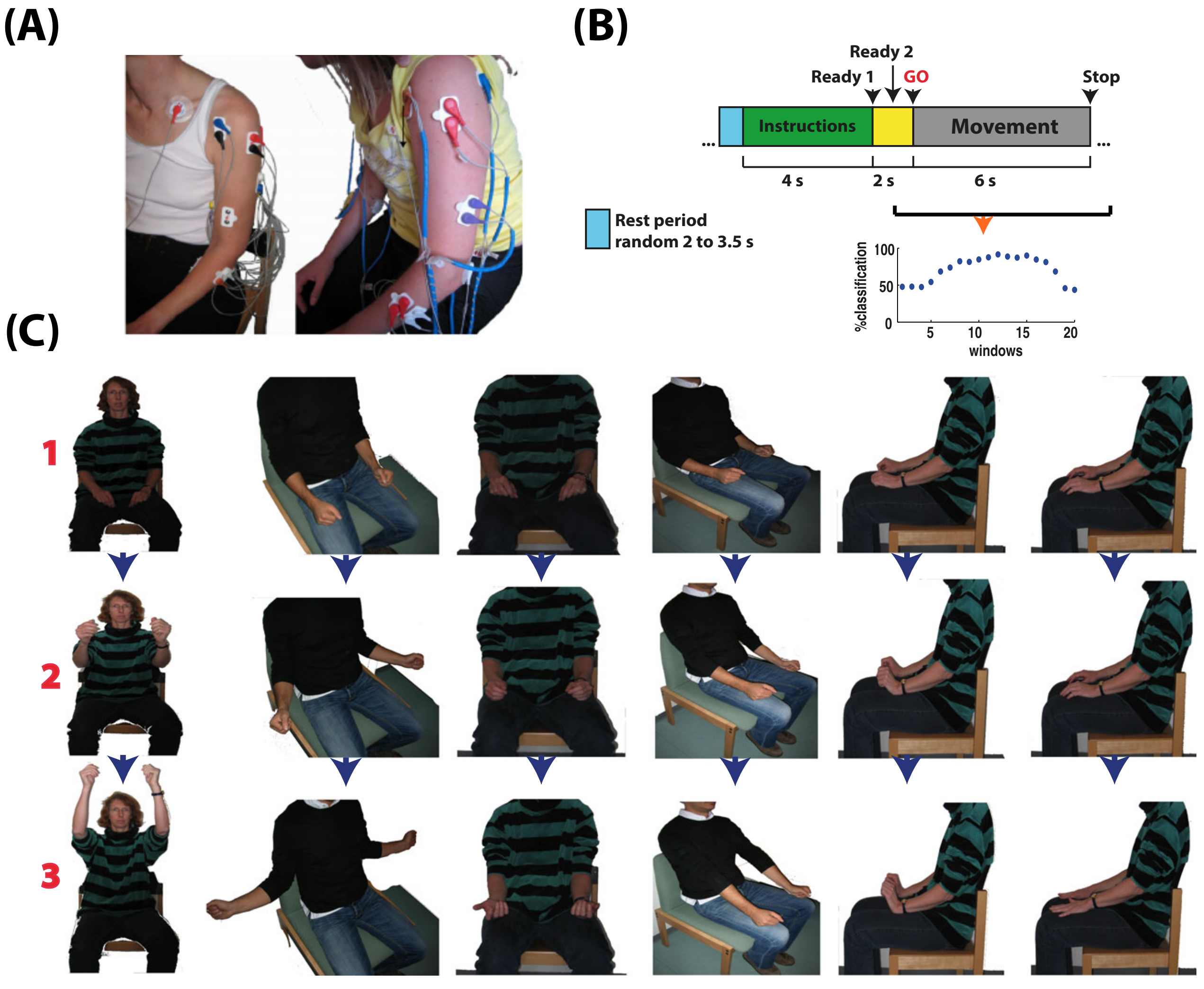


Figure 1. Experimental design. (A) Surface electromyography (EMG) electrodes placed on muscles involved in the six movements used during Fugl–Meyer Assessment test. (B) Experimental timing. After a randomized resting period (2 to 3.5 sec) a 4 sec instruction interval occurred in which patient was presented with three figures (items 1, 2 and 3) representing the movement to perform. A feed-forward multilayer perceptrons (MLPs) neural network with varying numbers of hidden layer neurons was used to decode the muscle activity. To overcome the intertrial difference in trajectory, classification was performed on 19 time windows from −1.5 to 7 sec relative to the "GO". (C) From left to right: shoulder flexion, external rotation of the shoulder, supination, extension of the elbow, wrist extension and finger extension. Immediately after the instructions period, two ready cues with 1 sec interval were presented to the patient before the "GO" cue appeared and the patient started to perform the movement at a comfortable pace. Patients were instructed to maintain the final posture until a "Stop" cue appeared.

period between 4 and 7 sec allowed the patients to return to the starting position (hands resting on their lap) (Fig. 1C item 1). Patients were instructed to perform each movement with both arms simultaneously maintaining their gaze on the screen, in order to avoid neglecting the nonaffected hand (or less affected[31]) due to a concentration shift toward the affected arm. Compensatory movements were discouraged. The experiment was divided into blocks. One block implies 60 trials, 10 for each of the six different movements. On average patients underwent between 4–6 blocks with a total amount of 40–60 trials per movement condition. An interblock rest break interval of 5–10 min was used in order to avoid muscle fatigue.

Data collection

Surface EMG (sEMG) data were acquired using a BrainAmp 32-channel amplifier from Brain Products GmbH, Munich Germany (10 patients) and a BrainAmp 16 bipolar EMG fMRI compatible amplifier from the same company (38 patients). Bipolar Ag/AgCl electrodes were used for surface EMG data acquisition and placed on the muscles involved in the six movements to be performed: (1) extensor carpi ulnaris (2) extensor digitorum (3) on the flexor carpi radialis, palmaris longus, flexor carpi ulnaris (flexion) (4) long head of the biceps (flexion) (5) the external head of the triceps (6) anterior portion of deltoid muscle (7) lateral portion of deltoid muscle and (8) posterior portion of deltoid over the teres minor and infraspinatus muscles (see Fig. 1A). When using the 32 channels unipolar amplifier, reference was placed at the olecranon. Ground was placed over the paretic side clavicle. The EMG electrodes impedance was always kept under 20 KΩ. The sampling rate was 2500 Hz. Auditory and visual cues were presented using E-prime software (Sharpsburg, PA, USA).

EMG-decoding

Compensatory movements

Although the patients were asked to avoid compensatory movements, different compensation strategies to reach the end point of each movement were observed. Therefore, trials where the trajectories showed an absence of muscle activity (due to patients' loss of attention to the task) or extreme variations were rejected (Data S1).

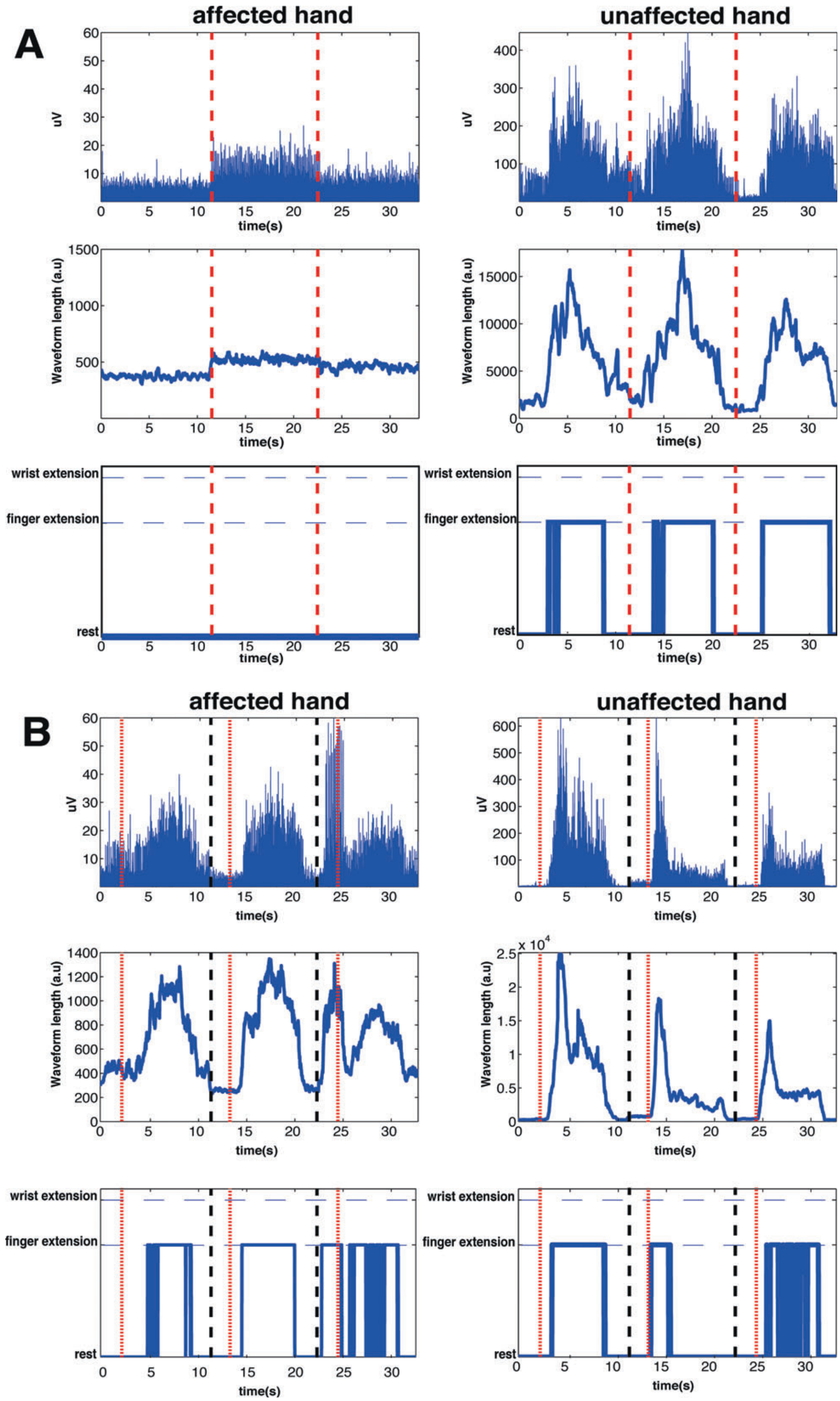
Decoding design

After the EMG was preprocessed (Fig. 2A and B upper panel) the waveform length (WL),[32] a time domain feature of the EMG signal providing a measure for signal amplitude and frequency, was calculated (Data S1) (Fig. 2A and B middle panel) and used to train the classifier.

A feed-forward multilayer perceptrons (MLPs) neural network with varying numbers of hidden layer neurons was used. To overcome the intertrial difference in trajectory, classification was performed on 19 time windows from -1.5 to 7 sec relative to the "GO" (Fig. 1B) and the highest decoding accuracy across windows was considered as the decoding accuracy for that movement (for more details see Data S1).

The decoding was performed for each upper limb separately for three categories of movements depending on the main muscles involved: (1) forearm muscles (hand and finger movements), (2) upper arm muscles (elbow and shoulder movements) and (3) all upper limb muscles (hand, fingers, elbow and shoulder movements). Furthermore, for each of these three movement categories we performed a classification using electrodes on: (1) forearm only (hand and wrist muscles), (2) upper arm only (biceps, triceps and shoulder muscles) and (3) entire arm (see an example of forearm movement decoding using forearm muscles in Fig. 2A and B lower panel). This was used to isolate the effect of different movement strategies and to perform a separate analysis for the paretic muscles. The same number of trials per movement category was selected for classification. In order to guarantee that primarily the EMG activity of the main muscles involved in each movement drove the classification, an analytic sensitivity analysis of the neuronal network was performed (see Data S1).

Figure 2. Electromyography (EMG) trajectories, feature extraction and classification from the extensor digitorum. The left and right columns represent data on the affected and unaffected side, respectively. Eleven seconds of EMG data from 2 sec before and 9 sec after the "GO" cue belonging to three finger extension tasks were concatenated. Vertical dashed lines represent the first ready cue and the red vertical line represents the "GO" cue. We can observe in the right column how the EMG starts increasing a few milliseconds after the "GO" cue. Three main figures are presented: preprocessed EMG, the waveform length and the output of the classifier. The output of the neural network indicates the class with the highest probability to be occurring (in our case 0-rest, 1-finger extension, 2-wrist extension). When using data from the unaffected hand the classifier assigned the highest probability correctly to rest and finger extension. (A) However, in the affected hand the classifier cannot decode finger extension and detects rest as the class with the highest probability to be occurring in a patient without residual muscle activity. (B) On the contrary, the output of the classifier was correctly assigned to rest and finger extension in the paretic limb of a patient with residual muscle activity.


A
affected hand
unaffected hand
uV
time(s)
Waveform length (a.u)
wrist extension
finger extension
rest
B
x 10^4

Motor function and EMG- decoding

Since it has been proposed before that severity of motor impairment influences decoding of muscle activity in stroke patients,[33] we separated the group of patients according to the functional scores for hand (hFMA ≥5 severe group; hFMA <5 extremely severe group), arm (aFMA ≥11 severe group; aFMA <11 extremely severe group) and their combination (cFMA ≥16 severe group; cFMA <16 extremely severe group) and calculated the difference in EMG decoding. EMG decoding results using the electrodes placed on the main muscles involved in each movement type (e.g. finger and wrist extension using forearm electrodes) were used.

Data analysis and statistics

The acquired data were exported and processed offline in MATLAB (The MathWorks) (Natick, MA, USA). All data were reported as mean values ± SD when indicated. Decoding accuracies of the classifier were evaluated by the percentage of correct answers of the classifier attempting to decode each requested task (e.g.: Decoding of forearm movements (pulling together the data for finger extension, wrist extension and rest) was done using forearm electrodes (extensor carpi ulnaris, extensor digitorum, and flexors). According to Figure 1B, each testing trial (of the pulled data set) was divided into 19 windows. For each window independently, classification accuracy was evaluated across trials. The maximum accuracy found across windows was used as the decoding accuracy for that particular patient). Statistical evaluations were performed using Mann–Whitney *U*-test (a nonparametric test) with 95% CI.

Results

Contribution of each group of electrodes to specific movement decoding

Decoding unaffected wrist and fingers extension yielded superior results with electrodes placed on the forearm only compared to electrodes placed on the upper arm in 87.80% of the patients, as expected (Table 2). In the affected limb, 48.78% of the patients presented superior results decoding wrist and finger extension movements using forearm electrodes only, compared to when using upper arm electrodes only. This implies that the most paretic muscles (hand and wrist extensors) presented either minimal to no residual EMG activity or no detectable EMG activity in 51.22% of the patients. On the other hand, when using EMG data recorded from fore- and upper arm muscles combined (all muscles), finger and wrist extension motions were better decoded in 97.56% and 100% of all patients for nonparetic and paretic arm, respectively compared to using only forearm electrodes (Table 2).

A similar effect was observed during elbow and shoulder movements. Although in this case, the EMG activity on the unaffected arm was better decoded using electrodes placed on forearm and upper arm muscles (all muscles), than using electrodes placed in upper arm only in all patients, indicating a positive effect of forearm muscle activity in the decoding of elbow and shoulder movements. On the affected arm, the effect was similar and for 92.68% of the patients, the muscle activity during elbow and shoulder movements, was decoded better using EMG signals recorded from all electrodes, compared to upper arm electrodes only. Decoding of elbow and shoulder movements led to better results in 100% (unaffected arm) and 97.56% (affected arm) of the patients, when using EMG activity from only upper arm muscles and from all electrodes, compared to when using forearm muscle activity only.

Forearm movements

We classified the EMG activity to be related to either: (1) finger extension, (2) wrist extension or (3) rest (decoding chance level 33%). Patients presented no residual hand extension. However, wrist and finger extension in the affected limb could be classified with an accuracy of 55.79 ± 14.78%, 56.57 ± 14.15% and 64.56 ± 15.44% when using EMG activity recorded from forearm muscles

Table 2. Percentage (%) of patients where decoding accuracies using the main group of muscles involved in each group of movements were above decoding accuracies using unrelated muscles.

	Decoding forearm movements using forearm muscles >		Decoding upper arm movements using upper arm muscles >		Decoding all movements using all muscles >	
	Using upper arm muscles	Using all muscles	Using forearm muscles	Using all muscles	Using forearm muscles	Using upper arm muscles
Affected side	48.78	9.76	100.00	7.32	97.56	92.68
Unaffected side	87.80	29.27	97.56	7.32	100.00	100.00

only, upper arm muscles only and all fore- and upper arm muscles, respectively. On the unaffected side, the decoding resulted in higher accuracy values as expected (see Table 3). We considered a performance of 65% as the lowest required for a reliable control of an orthotic device using discrete decoding online for a minimum of 3–7 classes (since it is around two times the chance level of our classifier with the lowest number of classes or movements to decode [33%]). Decoding accuracies above 65% were observed in 21.95% and in 51.22% of all patients when classifying forearm movements using EMG data acquired at affected and unaffected forearms, respectively.

Upper arm movements

We classified the EMG activity to be related to either: (1) shoulder flexion, (2) external rotation of the shoulder, (3) supination, (4) elbow extension, or (5) rest (decoding chance level 20%). Upper arm movements in the affected limb could be decoded with an accuracy of 37.20 ± 15.25%, 55.70 ± 15.49% and 62.52 ± 16.61% when using EMG activity recorded from forearm muscles only, upper arm muscles only and all muscles, respectively. On the unaffected side, the decoding resulted in higher accuracy values as expected (see Table 3). Decoding accuracies above 65% were observed when classifying five arm movements using EMG data acquired at paretic and nonparetic upper arm muscles in 26.83% and in 43.90% of all patients measured, respectively.

Forearm and upper arm movements

We classified the EMG activity to be related to either: (1) shoulder flexion, (2) external rotation of the shoulder, (3) elbow extension, (4) supination, (5) wrist extension, (6) finger extension or (7) rest, (decoding chance level 14.29%). These movements in the affected limb could be decoded with an accuracy of 31.93 ± 12.86%, 39.57 ± 14.21% and 47.09 ± 15.10% when using EMG activity recorded from forearm muscles only, upper arm muscles only and all muscles, respectively. On the unaffected side, again, the decoding resulted in higher accuracy values as expected (see Table 3). Decoding accuracies above 65% were observed when classifying 7 upper limb movements using EMG data acquired at paretic and nonparetic upper arm muscles in 14.63% and in 46.34% of all patients measured, respectively.

Significant muscle activity

In this section, we were expecting to observe the highest contribution (weights) of the different EMG electrodes in the decoding of muscle activity in the electrodes placed over the main muscles involved in each movement (i.e. electrodes over forearm extensors during wrist and finger extension, over biceps during pronation/supination, over triceps during elbow extension and over deltoid during shoulder flexion and external rotation of the shoulder) in order to guarantee that remaining contraction control of the paretic muscle was still present.

We observed in 78.05% of all patients that during hand and fingers extension the electrodes placed on the paretic forearm extensors muscles presented higher contribution in the decoding compared to the paretic flexors ruling out the possibility of flexor activity being the main or only decodable EMG activity. This was observed on the unaffected arm in 73.2% of the patients. However, only 40% of these patients who showed higher contribution of electrodes placed over extensors compared to electrodes placed over flexors during finger and wrist extension in the affected hand, showed the same in the unaffected hand. These results could be due to the use of 19 windows for the decoding and choosing automatically the

Table 3. Decoding accuracies (in %).

		Electrodes			
	Movements	Forearm	Upper arm	All	Chance level
Affected side	Forearm	55.79 ± 14.78	56.57 ± 14.15	64.56 ± 15.44	33
	Upper arm	37.20 ± 15.25	55.70 ± 15.49	62.52 ± 16.61	20
	All	31.93 ± 12.86	39.57 ± 14.21	47.09 ± 15.10	14.3
Unaffected side	Forearm	70.41 ± 14.35	62.36 ± 15.18	83.44 ± 8.35	33
	Upper arm	41.45 ± 18.09	65.35 ± 14.17	74.89 ± 10.83	20
	All	42.85 ± 15.73	47.32 ± 16	65.82 ± 14.81	14.3

Mean and standard deviations (SD) of decoding accuracies when decoding forearm, upper arm and complete arm movements. Results are divided depending on the placement of the electrodes used for the decoding: forearm (extensor carpi ulnaris and digitorum and flexor carpi radialis, palmaris longus and flexor carpi ulnaris), upper arm (long head of the biceps, external head of the triceps and anterior, lateral and posterior portion of deltoid muscle) and all combined.

one with the best decoding accuracy which could happen when patients started to close their hands if the timing was not respected and patients returned to start/resting position before the end of the trial.

When we grouped patients based on their hand impairment severity (severe hFMA ≥5 or extremely severe hFMA <5), almost all severely motor impaired patients ($N = 6$) presented higher weights on extensor than on flexor forearm muscles, both on unaffected (83.3%) and affected side (83.3%). In the extremely severely motor impaired patients ($N = 35$), we observed higher weights on extensor than on flexor forearm muscles in 71.4% of the patients in the unaffected arm and 77.1% of the patients in the affected arm.

As expected during the decoding of all movements using all electrodes, the electrodes placed on the upper arm presented a larger overall contribution, likely due to less impairment and the stronger more reliable EMG in upper arm muscles. The electrodes on top of the main muscles involved in each movement (e.g. triceps during elbow extension) generated always the higher contribution in all patients' unaffected arm. This was also the case for all patients' affected arm during upper arm movements. However, during finger and wrist extension decoding using all electrodes, 70.7% of the patients presented higher EMG electrode contribution on forearm muscles.

Functional scores and EMG decoding

Since it has been proposed before that severity of motor impairment influences decoding of muscle activity in stroke patients,[33] we divided the patients into severe and extreme severe groups based of their hFMA, aFMA and cFMA. We found significantly better EMG decoding in severe compared to extremely-severe patients during upper arm ($z = 2.3394$; $P = 0.019$) and all ($z = 2.1261$; $P = 0.0335$) movements when patients were divided in groups depending on their aFMA and cFMA scores confirming some preliminary results on moderately and severely affected stroke patients.[33,34] The difference in decoding between severe and extremely severe cases was not significant for hand and finger movements using forearm electrodes only ($z = 0.7931$; $P = 0.4277$) as expected due to our inclusion criteria of no residual finger extension, which resulted in a low number of patients in the severe group.

Discussion

The results of the present study indicate that severely impaired chronic stroke patients retain residual muscle activity in the paretic muscles and that this activity can be decoded during six different movements and rest demonstrating that some level of neuronal innervation remains preserved despite severe upper limb impairment. These findings may not only provide a basis for biofeedback training of the paretic muscles or similar procedures pioneered by Basmajian,[35] but also for the use of these signals to control rehabilitation devices or assistive robotics and functional electrical stimulation (meaning that training of natural muscle pattern activity is possible).

We report that decoding of forearm movements involving the severely paretic muscles was accurate (above 65%) in 46% of the patients (out of 41 patients). Furthermore, we excluded EMG activity from muscles not involved in the movement in most of the patients. However, in 29.3% of the patients, we found that decoding of forearm movements was biased to upper arm muscle activity and not forearm extensors, which indicates that in these patients either there was no residual EMG activity on the forearm extensor muscles or not enough sensitivity in our method to detect it. Consequently, research into other techniques such as high-density EMG arrays might be necessary to resolve this issue.[36]

We observed significantly better EMG decoding in severe compared to extremely severe patients during elbow and shoulder and upper limb movements, when patients were divided into two groups depending on their FMA, confirming previous results on mild to moderately affected stroke patients.[33,34]

The decoding results of forearm and upper arm movements demonstrate that EMG could be used as a control signal for rehabilitation (biofeedback, robotic, electrical stimulation) of the affected limbs in half of the patients with severe paralysis and extended cortical and/or subcortical lesions strengthening residual functioning of neuronal innervation.

Since it has been shown that electrical stimulation of muscles can produce near-normal lower limb forces after chronic stroke,[37] we assume that muscle paralysis is not the main cause of weakness but deterioration of the cortical descending and ascending fibers and its respective learned nonuse effect.[38] Our results suggest that most of our patients retained some corticomuscular connections despite severely paretic muscles, which can be inferred by the correct decoding of the residual muscle activity. Descending pathways link the brain to the spinal cord, allowing flexible transmission of commands for voluntary movement to spinal motoneurons. However, not only the influence of the mono-synaptically (i.e. corticospinal tract) but also the influence of multisynaptically connected spinal systems like reticulospinal[39] and rubrospinal[40] tracts are important to evaluate the degree of remaining voluntary muscle activity. Furthermore, medial reticulospinal tracts and some corticospinal fibers (10% to 15% of the fibers) do not cross to the other side and may control the ipsilateral limb from the intact hemisphere. Accordingly, this evidence together with our results suggest that some residual connections such as corticospinal, reticulospinal and/or rubrospinal are intact and contribute to the decoded residual EMG activity observed in flexor and extensor muscles in severely impaired stroke patients despite their inability to use those muscles for skilled movements.

Limitations

One fundamental limitation to the use of this EMG-based approach has been that only a few research groups have explored the existence and control of residual muscle activity of stroke patients′ paretic limbs.[33,34] However, these two studies did not control for muscle activity physiologically unrelated to the intended movement but to compensatory movements (e.g. contracting biceps when trying to extend fingers), thus biasing the decoding with involuntary pathological muscle activity. Furthermore, they involved a low number of patients ([33]with n = 20; with n = 12) from chronic[33] and acute[34] groups, consisting mainly of mild to moderately impaired patients (i.e. [34]with residual movement) reducing their findings statistical power. In these studies, high-density EMG electrodes were used (large number of electrodes in a very reduced area normally covering one muscle group only, e.g. forearm extensors) reducing the number of muscles recorded. Another important limitation in the use of EMG signals is that they are sensitive to electrode placement, interference from neighboring muscle signals, skin properties (e.g. sweat on the skin, pulse) and are also dependent on a person's neurological condition. Furthermore, patients with severe motor impairment after stroke exhibit an abnormal, uncoordinated muscle activation pattern,[41] thus if the EMG activity is not properly isolated from interference from neighboring muscle signals and compensatory activity, an EMG controlled robot could move in an undesired way. Therefore, following our decoding results (i.e. EMG activity from the upper arm usually not related to wrist and hand extension influenced the decoding results), activity from the specific main muscles responsible for each particular movement only should be used in the decoding of EMG activity in rehabilitation.

Additionally, in accordance with the experimental protocol, the addition of the classical music piece during the time interval to perform the movement (6 sec) might have resulted in a positive cofound increasing patients' performance. Furthermore, the 6-sec time to perform the task was chosen following empirical and subjective questioning of four test stroke patients. However, it might be desirable to extend this time interval for patients requiring longer time periods to properly perform impaired movements. Nevertheless, this time was kept constant to simplify signal processing and statistical analysis and to avoid muscle fatigue.

Future directions

Although our EMG decoding results are based on offline processing of the muscle signals, an online version of our decoder could be easily implemented as demonstrated previously in healthy humans and amputees.[26,42] After a calibration session and the subsequent offline processing, technical artifacts can be easily detected and eliminated (e.g. improving impedance by changing the pregelled bipolar electrodes and using frequency filters) and the motion artifacts can be detected automatically during the rehabilitation task. It has been demonstrated that intra and intersession variability using bipolar surface EMG sensors range from 3.8% to 18%,[43,44] which should not cause a critical decrease in decoding results. However, in a rehabilitation scenario we would expect an increase of EMG activity in time and therefore calibration between training sessions is needed. Further work on this line should be accomplished to provide severely paralyzed stroke patients with reliable and stable EMG controlled assistive and rehabilitation technologies[45] (like it has been shown in amputees).[46]

Conclusion

Here, we show that it is possible to decode residual EMG activity when severely affected chronic stroke patients attempt seven different upper arm and forearm movements, a first step to allow successful use of these signals as controllers of multimotion mechanical prosthesis and a demonstration of residual innervations to muscles that cannot produce movements but whose pattern of contraction can be controlled by the patient.

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Author Contributions

A. R., D. B., L. C. and N. B. designed the study; A. R., E. G., D. B. and W. C. performed the experiments, A. R., E. G. and A. W. analyzed the data, A. R., E. G., A. W., M. B., L. C. and N. B. wrote the paper. All the authors read and approved the manuscript.

Conflict of Interest

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Supplementary material and methods.