Identifying tasks to elicit maximum voluntary contraction in the muscles of the forearm

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Oluwalogbon O Akinnola, MEng[1]

Vasiliki Vardakastani, PhD[1]

Angela E Kedgley, PhD[1]*

[1]*Department of Bioengineering, Imperial College London, London, United Kingdom*

Email addresses:

OOA: o.akinnola16@imperial.ac.uk

VV: v.vardakastani13@imperial.ac.uk

AEK: akedgley@imperial.ac.uk

* Corresponding author:

Angela E Kedgley

Department of Bioengineering

Imperial College London

South Kensington Campus

London SW7 2AZ

Phone: +44 (0) 207 594 0747

Abstract

Maximum voluntary contractions (MVCs) are often used for the normalisation of electromyography data to enable comparison of signal patterns within and between study participants. Recommendations regarding the types of tasks that are needed to collect MVCs for the muscles of the forearm have been made, specifically advocating the use of resisted moment tasks to get better estimates of forearm MVCs. However, a protocol detailing which specific tasks to employ has yet to be published. Furthermore, the effects of limb dominance on the collection of MVCs have not been considered previously. Muscle activity was monitored while 23 participants performed nine isometric, resisted tasks. The tasks that are likely to elicit MVC in the flexor carpi ulnaris, flexor carpi radialis, flexor digitorum superficialis, extensor carpi ulnaris, extensor carpi radialis, extensor digitorum communis, and pronator teres were identified. Thus, targeted protocols can be designed to mitigate against fatigue. Hand dominance had limited effect, with differences being found only in the finger flexors and extensors ($p < 0.03$). Thus, use of the contralateral flexor digitorum superficialis and extensor digitorum communis muscles to obtain baselines for activation levels and patterns may not be appropriate.

Keywords: maximum voluntary contraction, electromyography, wrist, forearm

1. Introduction

Electromyography (EMG) is widely employed for the detection and analysis of muscle activity in the upper limb. To mitigate against sensitivities of the technique and to allow for both inter- and intra-subject data comparisons, EMG signals are normalised. Maximum voluntary contraction (MVC) signals have been recommended for normalisation (Burden, 2010). Clinically, MVCs for the forearm muscles that act on the wrist are collected during an isometric power grip task (Mogk and Keir, 2003). Ngo and Wells, (2016), however, found that a greater signal could be elicited for the muscles with a series of resisted moment exertions. However, they did not comment on which task was most likely to elicit MVC in a given muscle. To date, a protocol to obtain MVCs for the muscles of the forearm has not been published. Also of note, is that studies investigating upper limb EMG generally have focused on one limb. Either the dominant or non-dominant, right or left limb of each participant is commonly tested. However, this practice, may be inappropriate due to differences in hand strength (Farthing et al., 2005), anthropometric measures (Kaplan, 2016), muscle architecture (Fugyl-Meyer et al., 1982), and control strategies (Adam et al., 1998) between dominant and non-dominant hands.

The objective of this study was to build on the work of Ngo and Wells, (2016) by identifying tasks most likely to elicit MVC in seven muscles of the forearm for both dominant and non-dominant arms. The aim was to allow future researchers and clinicians to build robust, efficient protocols tailored to the muscles they are investigating. Employing fewer tasks reduces the time requirements of the protocol and reduces the risk of fatigue setting in and affecting the results of consequent tasks.

2. Materials and methods

2.1 Experimental design

Fourteen surface EMG sensors (Delsys Trigno, Natick, MA, USA) (De Luca et al., 2012) were used to monitor the activity of the flexor carpi ulnaris (FCU), flexor carpi radialis (FCR), flexor digitorum superficialis (FDS), extensor carpi ulnaris (ECU), extensor carpi radialis (ECR), extensor digitorum communis (EDC), and pronator teres (PT) muscles in the dominant and non-dominant arms of 23 participants, 13 female (1.67 ± 0.07 m; 62.0 ± 9.2 kg) and 10 male (1.76 ± 0.07 m; 76.4 ± 12.9 kg). The protocol for the study was adapted from the study conducted by Ngo and Wells (2016) and the number of participants was determined from a power analysis of the mean muscle activities in their study. Each participant performed nine isometric resisted tasks that were found to generate the highest activity in the muscles considered in this study (Figure 1). Participants were given a demonstration and the opportunity to briefly practice each task submaximally. Each task was performed once and lasted 5 seconds; participants were given encouragement throughout to exert as much as possible. Multiple tasks were required, as the tasks asked participants to generate forces in single direction, and only the muscles anatomically able to contribute to each task were likely to produce MVC during that task (Buchanan, 1995; Hoozemans and van Dieën, 2005).

2.2 Data processing

The EMG data were processed in MATLAB (MathsWork, Natick, MA, USA) using custom written code. Raw EMG datasets had their DC offset removed, were rectified, and were low-pass filtered with a cut-off frequency of 13 Hz (Robertson and Dowling, 2003). For each participant, the task that elicited the highest activity in each muscle was noted and tallied. The signal for each muscle was then normalised to its peak value from across all nine tasks.

For each task, the total normalised muscle activity was summed, to provide insight into co-contraction levels.

2.3 Data analysis

The median activity for each muscle in the nine tasks was used to identify the task most likely to elicit MVC. The Wilcoxon signed rank test was used to test for differences between the muscle activity of the dominant and non-dominant limbs. The Friedman test was used to compare muscle activity across tasks with the Tukey-Kramer test for multiple comparisons being used for post-hoc analysis. Significance for the two tests was defined as $p < 0.05$.

3. Results

The task most likely to elicit MVC for each muscle can be inferred from the percentage of people that produced MVC in the dominant and non-dominant limbs when performing each task (Figure 2). Plotting boxplots of the activity of each muscle in the tasks further elucidates which task is most likely to elicit maximal activity in a muscle. The ECR is an example of a muscle that clearly exerted MVC in one task (Figure 3). The ECR, ECU, and PT each had one task that was most likely to elicit MVC; the median activity for these muscles was 100% in the pull, ulnar pull, and the pronation tasks, respectively. The FCR produced its highest median activity in the pronation task, the FCU did the same in the grip task, and the EDC was most activated during the finger extension task, but these medians were all submaximal. The non-dominant FDS was most active in the pronation task and was similarly active in grip and pronation tasks for the dominant limb.

Differences were found between the dominant and non-dominant EDC and FDS in the finger flexion task, the EDC and FCU in the finger extension task, and the FDS in the grip, ulnar pull, and pronation tasks ($p < 0.03$). There were no differences in the levels of co-contraction between the dominant and non-dominant limbs (Figure 4).

4. Discussion

The data presented show which tasks are most likely to elicit MVC for a given muscle in both the dominant and non-dominant limbs. Like (Ngo and Wells, 2016), this study found that no one task elicited MVC for every muscle, nor did a task produce MVC in 100% of the population for any given muscle. The finger muscles tested were the only ones that showed differences in their activities between dominant and non-dominant limbs, the FDS being different in the greatest number of tasks. It has been found that the dominant hand employs different control strategies to the non-dominant hand to complete the same task, especially in grip (Adam et al., 1998; Noguchi et al., 2009). This could explain the difference in finger muscle activity given that grip was involved in seven of the nine tasks. It is hypothesised that differences in muscle coordination affect muscle activation, with the non-dominant limb being less efficient, thus requiring higher activity to accomplish the same task (Bagesteiro and Sainburg, 2002). Of the seven instances when there was a difference between the activity in the dominant and non-dominant limbs, the non-dominant limb was more active in five. Considering the co-contraction measures, although no statistical difference was found for any of the tasks, the p-value for the finger flexion task was 0.08, suggesting a trend towards increased activation in the non-dominant limb.

A limitation of this study is that it is was not possible to verify if participants were performing the tasks correctly. Whilst the tasks are designed to target muscles are anatomically able to contribute to the instructed motion, the participants may also have exerted force in other directions. For example, the ulnar pull task is meant to ensure the participants activate the

ECU and FCU by rotating the wrist ulnarly, but they could also potentially exert force in the dorsal direction by extending the wrist. Furthermore, it is difficult to ensure that a participant performs MVC. A task may target the muscles and the participant may perform it correctly but unfamiliarity with the motion, such as extending the fingers, may prevent them from performing MVC. Though efforts were made to mitigate against this, i.e. giving encouragement to the participant and providing a practice round for each task, these limitations persist whenever recording MVCs.

A further limitation of the study was the performance of single trial of each task. Performing repetitions would have helped determine if the tasks which generated MVC in each participant were repeatable and elucidate the effects, if any, of fatigue. A further study should be performed to investigate the repeatability of MVCs and determine the effects of fatigue on their collection.

5. Conclusion

The objective of the study was to build on the study of (Ngo and Wells, 2016) by identifying which tasks were most likely to elicit MVC in seven muscles of the forearm in both the dominant and non-dominant arms. From the data collected, a targeted protocol can be designed for the ECU, EDC, ECR, FCU, FDS, FCR, and/or PT. This allows for studies to be task efficient, mitigating against fatigue, and can help with optimising sensor placement by using appropriate tasks to identify the muscles. Furthermore, when collecting MVCs for the fingers, dominance should be considered, and it may be inappropriate to use the contralateral limb as a baseline in cases of pathology.

Conflict of interest statement

The authors have no conflicts of interest to declare.

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Figures

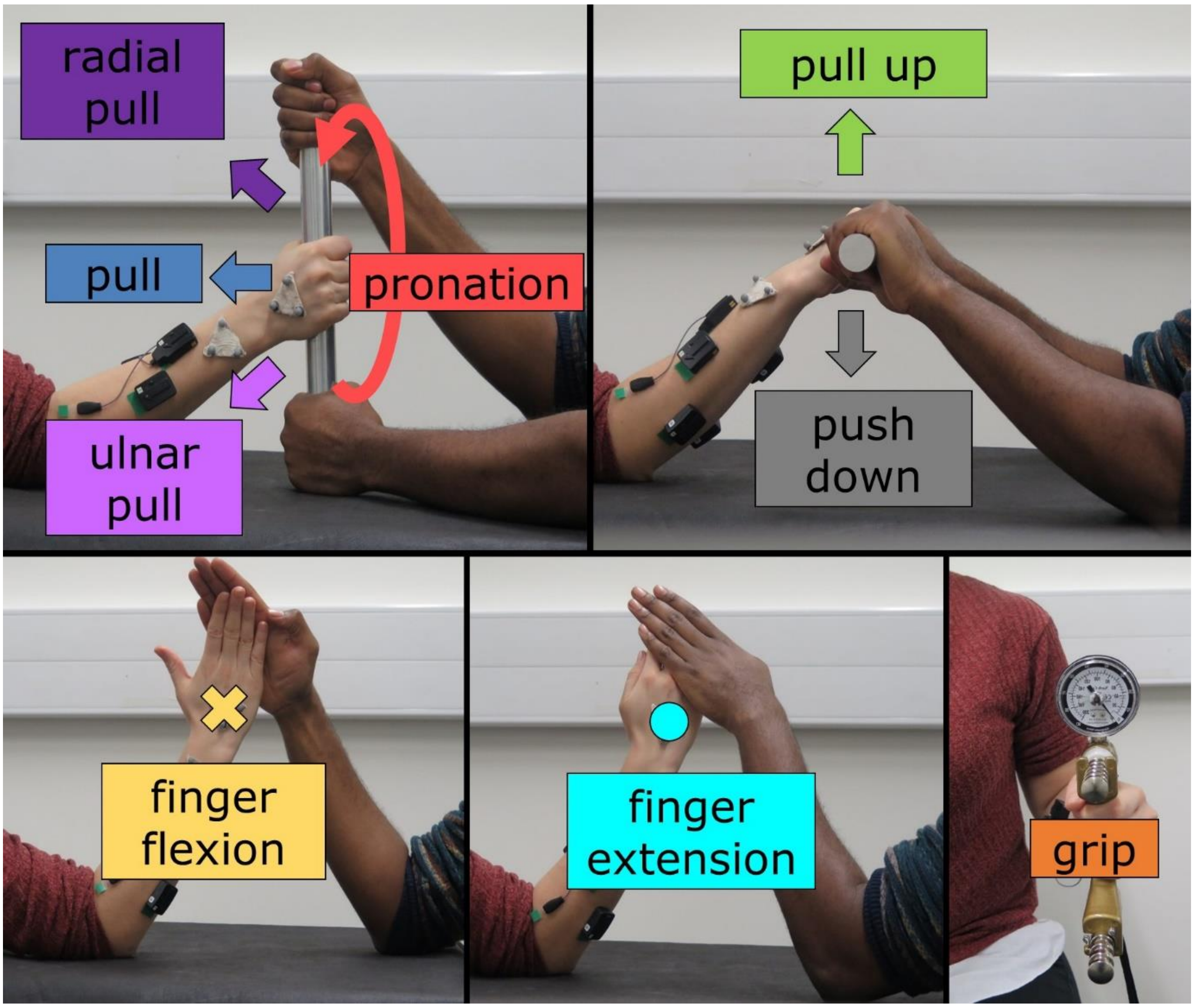

Figure 1: The nine tasks performed to capture the maximum voluntary contractions for the flexor carpi ulnaris, flexor carpi radialis, flexor digitorum superficialis, extensor carpi ulnaris, extensor carpi radialis, extensor digitorum communis, and pronator teres muscles.

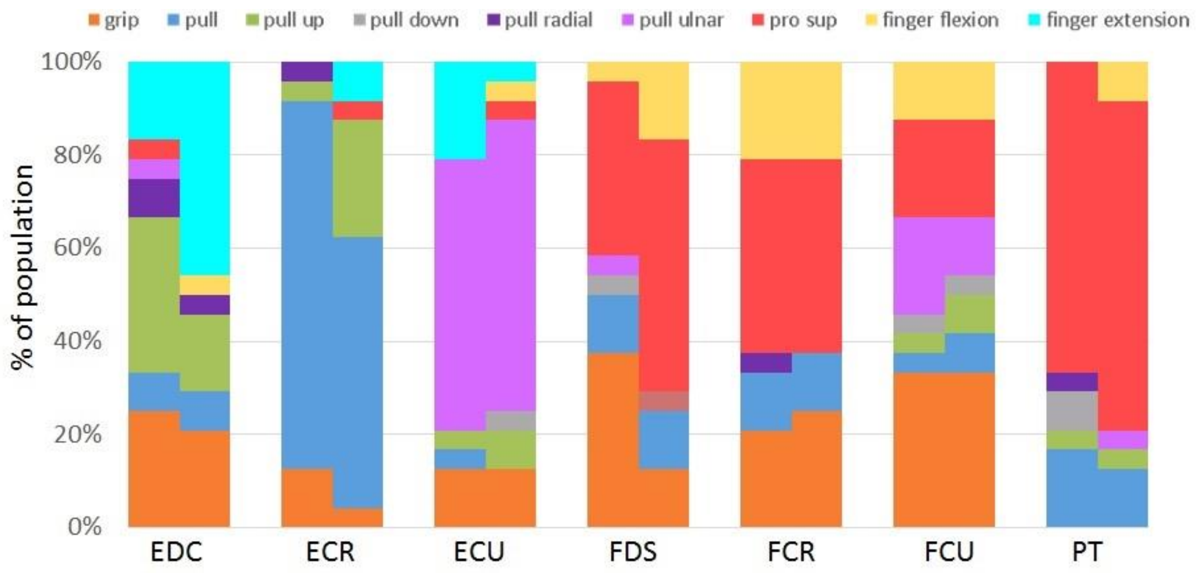

Figure 2: The percentage of people that generated maximum voluntary contraction for the extensor digitorum communis (EDC), extensor carpi radialis (ECR), extensor carpi ulnaris (ECU), flexor digitorum superficialis (FDS), flexor carpi radialis (FCR, flexor carpi ulnaris (FCU), and pronator teres (PT) muscles in the dominant (left bar) and non-dominant (right bar) limbs for all nine tasks.

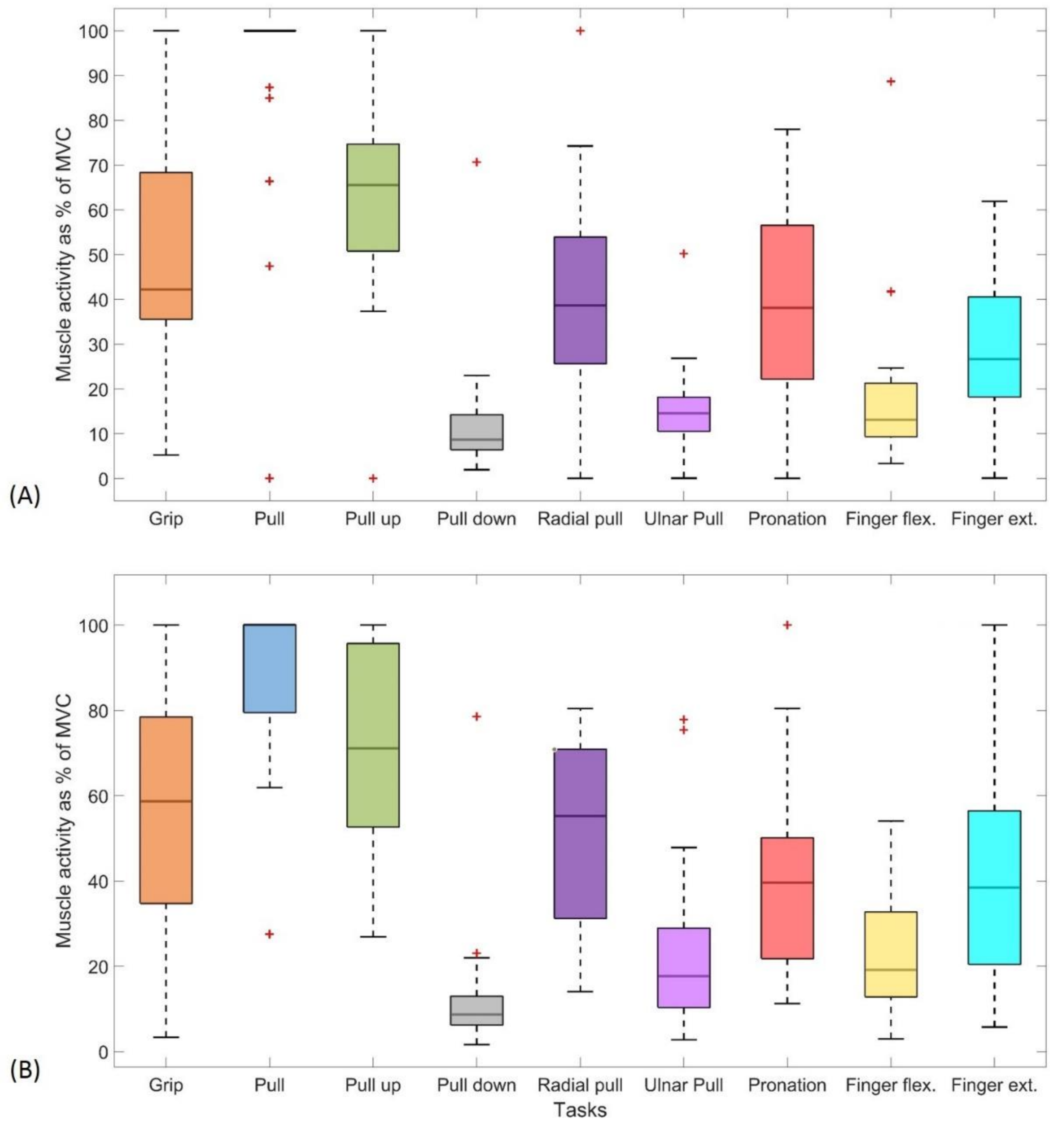

Figure 3: The muscle activity expressed as a percent of maximum voluntary contraction (MVC) of the (A) dominant and (B) non-dominant extensor carpi radialis for all the

170 population in the nine tasks. The extensor carpi radialis is shown as it was a muscle that clearly exerted MVC in one task.

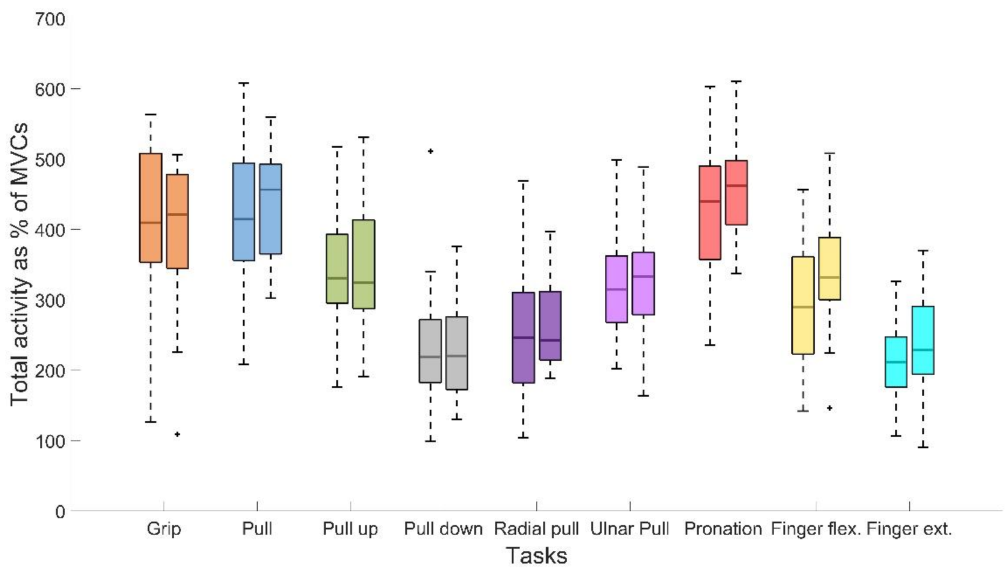

Figure 4: The total muscle activity as a percent of maximum voluntary contraction (MVC) for the dominant (left bar) and non-dominant (right bar) limbs for all nine tasks.