# WHICH ARE THE MINIMUM ACTIVITIES OF DAILY LIVING TO REPRESENT FOREARM MUSCLE ACTIVITY?

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## Introduction

Assessing muscle activity of the forearm muscles during the performance of activities of daily living (ADLs) is important to understand muscle function, to identify muscle imbalances, in determining the effectiveness of rehabilitation interventions or the potential risk of injury, and to develop and evaluate assistive devices [1,2]. However, its applicability would benefit from reducing the number of tasks to be measured in a controlled environment and with a reduced cost of time. A recent work [3] identified a set of 10 tasks representative of the hand kinematics during ADLs. The aim of this work is identifying a small set of tasks representative of the forearm muscular activity during ADLs.

## Material and Methods

We used the KIN-MUS UJI dataset [4] which contains recordings of muscle activities (7 channels) of 22 participants during the execution of 26 varied activities of daily living (Table 1). Muscle EMG was recorded using surface EMG bipolar electrodes and muscle activities were computed normalising EMG with the maximal values across all records for each subject. Their locations were chosen to maximize the extraction of information generated by the forearm muscles [4]. The recorded ADLs include 26 actions, most of them included in the Sollerman Hand Function Test (SHFT), commonly used to assess hand function in clinical settings and involve the interaction with objects of different sizes and weights. First, each record was rescaled to 1000 frames, and statistics (mean and range) were obtained from all data and each spot ($^{26}$STATS). Then, an iterative method was followed [3]: in each step, the data was reduced by removing each ADL data one-by-one, and the resulting N datasets were used to obtain N mean and range values for each spot (values obtained per each ADL; $N = 26 - k$, in the k-th step). In each step, the dataset explaining highest mean and range values was selected as input for the next step. This iteration was repeated until one ADL remained.

## Results

Figure 1 shows the worst-case statistic (that statistic that least resembles the original) respect to the $^{26}$STATS, for each step of the iterative ADL removal. With only 3 ADL (#10, #11 and #14) the mean and range values of all the spots were equal or slightly higher than the statistics obtained from all the ADLs. Table 1 shows the statistics ($^{3}$STATS) from this set of 3 ADLs and those obtained from $^{26}$STATS. Mean muscular activity values from $^{3}$STATS are slightly higher than $^{26}$STATS, and range values are very similar.

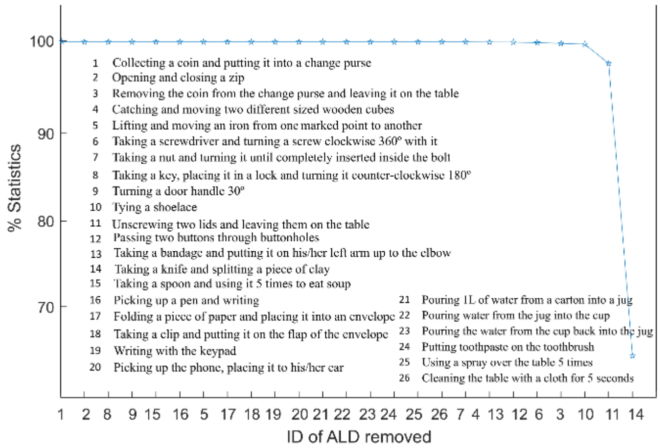


*Figure 1: List of ADLs and plot of worst-case statistic reduction in each step of the iterative ADL removal.*

| | $^{26}$STATS | | $^{3}$STATS | |
|---|---|---|---|---|
| SPOT | Mean | Range | Mean | Range |
| 1 | 0,137 | 0,997 | 0,187 | 0,995 |
| 2 | 0,075 | 0,998 | 0,104 | 0,997 |
| 3 | 0,082 | 0,997 | 0,111 | 0,996 |
| 4 | 0,148 | 0,997 | 0,203 | 0,994 |
| 5 | 0,178 | 1,000 | 0,237 | 1,000 |
| 6 | 0,199 | 1,000 | 0,260 | 0,999 |
| 7 | 0,134 | 0,992 | 0,165 | 0,991 |

*Table 1: Statistics (mean and range)of normalized sEMG on each spot across all the ADL ($^{26}$STATS) and across the last 3ADL obtained from the iterative method ($^{3}$STATS).*

## Discussion

The results suggest that a set with only 3 ADLs (Tying a shoelace, unscrewing two leads and cutting with a knife) could be enough to assess forearm muscle activity underlying ADL, with high level of similarity to those considering a wide set of varied ADL. Unscrewing two leads and cutting with a knife are already part of the activities included in the set of 10 activities representative of kinematics during ADL [3]. Therefore, adding the task of tying a shoelace could complete the set to be representative of both hand kinematics and muscle activity during ADL.

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## References

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