Motor Unit Tracking Using High Density Surface Electromyography (HDsEMG)

Automated Correction of Electrode Displacement Errors

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Summary
Introduction: This article is part of the Focus Theme of Methods of Information in Medicine on “Biosignal Interpretation: Advanced Methods for Neural Signals and Images”.

Objectives: The study discusses a technique to automatically correct for effects of electrode grid displacement across serial surface EMG measurements with high-density electrode arrays (HDsEMG). The goal is to match motor unit signatures from subsequent measurements and by this, achieve automated motor unit tracking.

Methods: Test recordings of voluntary muscle contractions using HDsEMG were performed on three healthy individuals. Electrode grid displacements were mimicked in repeated recordings while measuring the exact position of the grid. A concept of accounting for translational and rotational displacements by making the projection of the recorded motor unit action potentials is first introduced. Then, this concept was tested for the performed measurements attempting the automated matching of the similar motor unit action potentials across different trials.

Results: The ability to perform automated correction (projection) of the isolated motor unit action potentials was first shown using large angular displacements. Then, for accidental (small) displacements of the recording grid, the ability to automatically track motor units across different measurement trials was shown. It was possible to track 10–15% of identified motor units.

Conclusions: This proof of concept study demonstrates an automated correction allowing the identification of an increased number of same motor unit action potentials across different measurements. By this, great potential is demonstrated for assisting motor unit tracking studies, indicating that otherwise electrode displacements cannot always be precisely described.

1. Introduction

Motor units (MUs) are the smallest functional units of the peripheral motor nerve system. Neuromuscular diseases affect MUs, either directly or indirectly. The follow-up study of MUs during a disease process may, therefore, improve our understanding of neuromuscular diseases. Recently, MU tracking using high-density surface electromyography (HDsEMG) has been introduced as a neurophysiological technique that enables noninvasive follow-up of single MUs [1]. In this technique MU action potentials (MUAPs) are recorded with an array of densely spaced electrodes after electrical stimulation of the afferent nerve. In these HDsEMG recordings, each MUAP is presented as a spatio-temporal profile or fingerprint of the corresponding MU. Use of the characteristic information in the fingerprints facilitates detection of the MUAPs in consecutive recording sessions and, hence, allows for MU tracking.

MU tracking may provide insight into the relationship between MUAP properties and how these are affected during disease progression. However, before changes in a MUAP fingerprint between sessions can be ascribed to an underlying pathophysiological process, other factors that affect it have to be taken into account. It is known that MUAP properties depend on geometrical and anatomical factors such as muscle fiber length, signal stability (electrode-skin contact), electrode location, and electrode
orientation [2]. In particular, even small shifts in electrode position can affect the MUAP parameters significantly.

In clinical practice, the recording grid can be rotated, translated and bended in a different way compared to how it was attached in the previous recording session. In [3], a method was proposed to correct for translational errors for the study of the external sphincter muscle. In this study we extend this correction procedure and show how the effects of rotation between sessions can be automatically compensated for. We illustrate the approach on a low-force voluntary contraction measurement of thenar muscles, following well-defined displacements.

2. Methods
2.1 Recordings
Test recordings of voluntary contractions were performed on three healthy subjects using a HDsEMG grid with 126 electrodes. The diameter of the electrodes was 1.5 mm and they were spaced equidistantly in 9 rows and 14 columns with inter-electrode distance of 4 mm, as described in detail elsewhere [1]. The grid was placed over the thenar muscles. Initially, four configurations were introduced to illustrate the concept using recordings from a single subject, indicated in Figure 1a. Additionally, recording grid in configuration 1 was used as a reference configuration for 5 additional 2-minute recordings in each of 3 subjects: with the grid positioned in reference configuration, and positions rotated for –5, +5, –10 and +10 degrees around it, mimicking accidental grid displacements. The approximate reference position (configuration 1) is identified as the orthogonal to the direction connecting carpometacarpal (CMC) and metacarpophalangeal (MCP) joints of the thumb. This guaranteed the total thenar muscle coverage.

In the experimental setup, it was important to ensure that the position of the electrode grid was precise, especially in cases of small (intentional) displacements.

For this precise positioning, a double-sided adhesive tape containing small and large gaps was used, with the detailed procedure described in [4].
Recordings were performed on a single day for each subject, with half-hour break intervals. Visual feedback in the form of bi-polarly filtered signals was used to assist the subject in establishing and maintaining a stable, low-force contraction level, estimated at 1–5% Maximum Voluntary Contraction (MVC).

All signals were first decomposed automatically, separating each into contributions from individual MUs using the algorithm described and verified in [5] and [6]. First part of this algorithm [6], responsible for MUAP fingerprint extraction using optimal clustering was utilized. This yielded sets of MUAP fingerprints for each session.

Fingerprints that were observed at least 100 times without being superimposed to other MU fingerprints (uncorrupted) during the two-minute recording were considered reliable, averaged and kept for further analysis.

2.2 Artificial Recording Grid Displacement

To assess the effect of rotation of a grid around its center, we first assign coordinates \((x, y)\) to the electrode locations in the original grid placement. After rotation over angle \(\theta\), new coordinates \((x', y')\), representing the position of these electrodes are then obtained by multiplication with a rotation matrix:

\[
\begin{bmatrix}
  x' \\
  y'
\end{bmatrix} = \begin{bmatrix}
  \cos \theta & -\sin \theta \\
  \sin \theta & \cos \theta
\end{bmatrix} \begin{bmatrix}
  x \\
  y
\end{bmatrix} \tag{1}
\]

To assess the value of a fingerprint in every set of rotated coordinates \((x', y')\), we use the linear interpolation based on originally recorded values. This was done for each temporal sample to obtain a projection of a fingerprint on a rotated grid. The rotation procedure is depicted in Figure 2a. The interpolation is reliable only in the intersection area (gray) that represents the same physical surface covered by the grid in both recordings, while the rest of the values cannot be reliably assessed and were put to zero.

Apart from rotation, the in-plane translation of the recording grid is practically inevitable and thus has to be taken into account [3]. This translation describes a final transformation of grid coordinates:

\[
\begin{bmatrix}
  x'' \\
  y''
\end{bmatrix} = \begin{bmatrix}
  x' \\
  y'
\end{bmatrix} + \begin{bmatrix}
  \Delta x \\
  \Delta y
\end{bmatrix} \tag{2}
\]

Comparing translated observations can be done only in the intersection area (gray in Figure 2b). Since we can compare only part of each fingerprint, it is necessary to choose a “subgrid” \(-6 \times 6\) subset of electrodes around the place of the highest spike which is subsequently used for comparison. The subgrid “subfingerprint” is compared with each possible counterpart of the investigated fingerprint with which we attempt to match. The best possible position reveals the translation. This example is shown in Figure 2b.

The minimal translational step in both \(x\) and \(y\) directions naturally equals to one inter-electrode distance. This brings a limitation due to the fact that a shifted electrode can measure potentials anywhere between two neighboring electrodes. We exploit the property that the potentials between close electrodes can be assessed correctly due to the dense electrode placement of our recording grid. Therefore, we up-sample the signal four times using bicubic interpolation ([7]) of the measured neighboring potentials to increase the translation resolution.

Each fingerprint is upsampled and rotated for a chosen angle, followed by the estimation of optimal translation for the comparison with its “non-rotated” counterpart. We proceed with downsampling the signal to its original dimensions, and then compare rotated and “fixed” fingerprints using two parameters: Pearson correlation coefficient and normalized mean squared error (NRMSE). NRMSE is calcu-
Figure 4  Matching the units from displaced grid recordings: (a) MUAP fingerprint obtained using grid rotated over 42° with respect to signature from (b); (c) overlaid signatures from (a) and (b) without applying correction spatial transforms (d) after transform: overlaid signatures (b) – red and (c) – black; (e) matching corrected projection of (a) using the operators described in the text to identify matching indicated in (d); subgrid used to pinpoint the translation displacement is depicted in gray.
lated using ▶Formula 3, where \( z \) represents the estimated shape obtained by clustering, and \( z \) the template (exact) form. Summation is performed over all samples and channels. The peak of the ratio between these values (high correlation and small residue when we subtract fingerprints) indicates units that match. Each MUAP fingerprint obtained by a “displaced” grid is compared with its best match from the “fixed” grid measurement.

\[
NRMSE = \sqrt{\frac{\sum (\hat{z} - z)^2}{\sum z^2}},
\]

The complete procedure goes as follows: the rotation angle is varied and the optimal translation is calculated until the best overall result is achieved. Fine tuning is then applied around the indicated angle to pinpoint a correct value. The output provides the angle of rotation and the displacement in \( x \) and \( y \) directions.

3. Results

For the study with four configurations (▶Figure 1a) in total, 25 reliable MU fingerprints were extracted with the decomposition method. Out of these, three units could be tracked across measurements: one unit appeared in three configurations (1, 2, 4), and the remaining two were matched across configurations 1 and 2. An example for the automated correction of the specified 45 degrees displacement is portrayed in ▶Figure 3, showing the correlation and the ratio between correlation and NRMSE. The angle was estimated at 42 degrees, translation at \( -2 \) and 3 mm displacement in \( x \) and \( y \) directions respectively. ▶Figure 4a and ▶Figure 4b indicate the originally recorded fingerprints from positions 2 and 1 respectively. Seemingly different units (▶Figure 4c) match almost perfectly once the rotational and translational corrections have been applied (▶Figure 4d). Part of the procedure used to identify translational displacement following the rotation can be seen in ▶Figure 4 f. The subgrid used for comparison is also indicated.

The second part of the study involved three subjects and aimed at MU tracking comparison is also indicated. The displacement following the rotation can be the procedure used to identify translational differences. The table provides ▶Table 2 provides the ratios of agreement revealed the angular amplitude of 1.6 degrees. ▶Table 2 provides ranges for angular and translational displacements.

4. Discussion

Even when electrode re-placement between sessions is done with great care, re-positioning errors may remain. Mitigating the effect of such errors may be expected to improve the reliability of ascribing changes in the MUAP to true (patho) physiological changes. Extrapolating the results of our pilot study with known displacements indicates how this may be achieved when the replacement error is not known.

Thus far, MU tracking using HDsEMG has been performed without corrections for recording grid displacement [1] or accounting for translational displacements only [3]. This implied that correlations between identical but displaced MUAPs could be relatively low; indeed, the threshold for considering MUAPs to be similar was set to a correlation value of 80% [1, 3].

### Table 1

Comparison of the fingerprints from measurements with displaced (rotated and translated) electrode grid, before and after applying the in-plane projection adjustment

<table>
<thead>
<tr>
<th>Subject</th>
<th>Extracted</th>
<th>Trackable</th>
<th>Before correction (%)</th>
<th>After correction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>51</td>
<td>8</td>
<td>86.3</td>
<td>92.4</td>
</tr>
<tr>
<td>2</td>
<td>39</td>
<td>6</td>
<td>84.0</td>
<td>93.4</td>
</tr>
<tr>
<td>3</td>
<td>30</td>
<td>3</td>
<td>82.2</td>
<td>90.0</td>
</tr>
</tbody>
</table>

One should note that translational difference values (▶Table 2) could be provided up to the resolution of the adjustment step: 1/4 of IED (1 mm) in both directions. Angular displacements should be observed with caution due to the previously indicated (but single case) angular ambiguity.

### Table 2

Ranges for measured displacements and comparison with the indicated values for all subjects

<table>
<thead>
<tr>
<th>Subject</th>
<th>Average angular displacement difference* (˚)</th>
<th>Translational difference** (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>X direction</td>
</tr>
<tr>
<td>1</td>
<td>((-1.1)–7)</td>
<td>1–4</td>
</tr>
<tr>
<td>2</td>
<td>((-2)–(-3))</td>
<td>2–8</td>
</tr>
<tr>
<td>3</td>
<td>(0.7–4)</td>
<td>1–6</td>
</tr>
</tbody>
</table>

*provided as a range of values of differences between an indicated and calculated angles

**provided as a range of absolute values measured in different displacements
Being able to automatically adjust for replacement errors might allow for a higher threshold, increasing the specificity. It may also simplify greatly the otherwise strict and time consuming procedure for placing the HDsEMG recording grid. Furthermore, in our study, correlations of > 80% did not necessarily mean fingerprints could be considered the same (data not shown) as was observed with visual inspections.

Therefore, we opted to add NRMSE to measure (dis)similarity as well. While correlation reflects similarity in shape, NRMSE addresses the relative residue when two shapes are subtracted from one another. This ratio therefore optimizes on matching criteria between MUAPs to minimize the detected similarity between objectively different shapes. NRMSE might even substitute correlation altogether in future MU tracking studies, since it proved more sensitive for fine corrections. However, this would have to be previously thoroughly checked for unforeseen errors having a large and diverse base of MUAP shapes.

After adjusting the projection using rotational and translational operators, significant improvement in agreement was observed both visually and numerically via the correlation and NRMSE coefficients. Moreover, it was found that this method allows fine-tuning in the order of two degrees in angular direction in rotation and a quarter of the inter-electrode distance accuracy in translation. The correction procedure maximizes correlations between units in different sessions. Hard thresholding on these correlation parameters did not enable fully automated matching in a sense that the visual confirmation on indicated “similar” units was still necessary. Further insight into methods for rotation and translation invariant pattern classification might provide more reliable measures for this purpose (e.g. [8]). To define the necessary agreement between fingerprints in order to consider them as originating from the same MU, the minimal disagreement between different MUAPs has to be described. Also, it is important to investigate and describe the changes that could be ascribed to the remaining modeling imperfections such as bending of the electrode grid, and changes in skin-electrode contact. These are likely to result with muscle-specific correction functions that take into account both the physiology as well as the overall geometry of the recording grid. An obvious starting point would be to include proven MUAP propagation models [9–11]. These would enable to differentiate between the physiological changes of the muscle, increase the method performance and define its exact limitations when comparing healthy units. This rule would help to maximize the applicability of MU tracking studies.

We addressed the group of complex hand Thenar muscles. It is probable that MU tracking would prove much easier and applicable on other muscles and thus, enable qualitative increase in these tracking efforts. Also, metrics’ other than NRMSE and correlation, for comparison of this specific type of shapes, that would take into account also physiological limitations, would be highly welcome. Difficulties for introducing any new metric are related to its (preferred) intuitive character and wide acceptance that is needed for comparison of different studies.

Finally, this proof of concept study was demonstrated on the case of voluntary contractions, granting relatively small number of traceable MUs. This can be explained by several reasons: 1) low force voluntary contractions do not strictly guarantee activations of same MUs; 2) a number of units had to be omitted due to larger interference (overlap) with other MUs; and 3) shapes that could arguably belong to the same MUs did not sufficiently match, possibly due to model imperfections that disregarded bending of the grid for these very complex muscles. However, in real MU tracking practice, electrically stimulated recordings would likely take place instead of voluntary contractions. These would enable more precise tracking (accessing limited number of MUs at the same time) and eliminate the need for decomposition avoiding obstacles related to it.

5. Conclusions

We presented a method to track MUs across measurements more reliably when a recording grid is potentially not perfectly repositioned. The initial results show that the method reliably aligns MUs across sessions. This will allow MU tracking with higher precision than currently possible.

Acknowledgments

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References