Motor unit editing time in high-density EMG decomposition decreases with the operator's experience and pulse-to-noise ratio but does not depend on simulated muscle

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Abstract. *Manual editing of decomposition results represents an important but time-costly aspect of motor unit (MU) identification from a high-density surface electromyogram (hdEMG). We analysed the editing time and number of actions used to manually edit the decomposition results in synthetic signals. We simulated the Biceps Brachii (BB) and Soleus (SO) muscles at four different contraction levels: 10%, 30%, 50%, and 70% of maximum voluntary contraction (MVC). Gaussian noise was added at three signal-to-noise ratios (SNR): 15 dB, 20 dB, and Inf dB. Signals were decomposed into individual MU contributions using the Convolutional Kernel Compensation (CKC) method. The initial Pulse-to-Noise Ratio (PNR) was calculated to estimate automatic MU identification accuracy.*

Nine operators with different levels of experience and research backgrounds manually edited the decomposition results. Log files were created to determine the time needed to edit MU, the number of all used actions, and add or delete MU discharge actions.

The initial PNR value of MUs and SNR correlated with editing time, number of all used actions, add actions and delete actions. Contraction level and muscle were not significant factors. The operator's background and category, on the other hand, influenced the editing time and the number of used actions.

1 Introduction

High-density surface electromyograms (hdEMG) are extensively used in research fields such as sports science [9], rehabilitation [3] and physiotherapy [11]. The decomposition of the hdEMG enables valuable insight into the behaviour of motor units (MUs). A MU consists of an alpha motor neuron and its innervated muscle tissue. With the decomposition of hdEMG, we can observe neural codes from the central nervous system and shapes of MU action potentials (MUAPs), which contain all the anatomic and geometric information about the muscle we are investigating.

The automatic decomposition algorithms using the blind source separation principles [6] decompose hdEMG without knowing the experimental protocol, the measured subject, or the acquired signal quality. Therefore, a human operator must manually inspect the decomposition results and improve the segmentation of identified MU spikes into MU discharges. The latter includes optimising the MU filter identified by the automatic decomposition techniques. Even though the goal of manual editing is clear, and there are many tutorials on how to edit the decomposition results properly [1], there are still many situations where the classification of MU discharges is not a trivial decision.

In this study, we investigated how editing strategies and time spent to edit one MU depend on the experiences of a human operator and properties of the hdEMG signal: pulse-to-noise ratio (PNR), level of muscle contraction, muscle, and signal-to-noise ratio (SNR).

2 Methods

2.1 Signal dataset

We simulated synthetic signals of Soleus (SO) and Biceps Brachii (BB) muscles. In SO, 200 MUs were simulated using the simulator in [2]. In BB, 200 MUs were simulated using the simulator in [4]. Two different muscle realisations were simulated for each muscle type with randomly distributed MU territories in each realisation.

MU discharge patterns were generated by the model described in [5]. The MU size and the recruitment threshold were exponentially distributed, with many small and low-threshold MUs and exponentially fewer large and high-threshold MUs. The length of contractions was set to 20 s, and contraction levels were set to 10%, 30%, 50% and 70% of maximum voluntary contraction (MVC). The hdEMG signals were detected by the 9×10 electrode array. Three different SNRs were simulated (15, 20, and Inf dB). Altogether, there were 48 simulated signals (24 for SO and 24 for BB muscle).

2.2 Automatic decomposition

All signals were decomposed using the automatic Convolution Kernel Compensation (CKC) method [9], built into the DEMUSE tool, version 6.3. The following settings were used for automatic decomposition: 50 decomposition runs, band-pass filtering of hdEMG signals with the 4th order Butterworth filter (20-500 Hz),

no spatial filtering applied, and automatic selection of 95% of best quality hdEMG channels. CKC decomposition yielded 17.6 ± 3.5 (SO) and 8.6 ± 3.8 MUs (BB). The average initial PNR value was 40.1 ± 12 dB for SO and 33.4 ± 8.9 dB for BB.

2.3 Human operators

Nine human operators (co-authors of this contribution) with different levels of experience and different background knowledge edited the same set of hdEMG signals. We divided operators into three levels of experience based on the estimated number of previously edited signals (Table 1). The operators were all familiar with the manual editing process and all the functionalities available in the DEMUSE tool [7].

Table 1. Human operators with experience level, number of edited signals, and background (PHY – Physiology, CS – Computer Science).

Operator	Level of experience	No. of edited signals	Background
O1	Beginner	10 - 50	PHY
O2	Beginner	10 - 50	PHY
O3	Beginner	10 - 50	CS
O4	Beginner	10 - 50	CS
O5	Semi-experienced	51-1000	CS
O6	Semi-experienced	51-1000	CS
O7	Semi-experienced	51-1000	PHY
O8	Expert	> 1000	CS
O9	Expert	> 1000	PHY

2.4 Experimental protocol

To standardise the editing process, all the operators were required to read a short manual. To accurately measure the editing time, they were asked to use a particular version of DEMUSE, which automatically generated log files that included information on used actions and their corresponding timestamps. Log files were used to calculate the editing time per MU, the number of all actions per MU, the number of actions used to add MU discharges (add actions), and the number of actions used to remove MU discharges (delete actions).

Statistical analysis was performed using the linear mixed models (lmer) in RStudio using lmer4 package. All results were transformed using the log transformation to make the residuals normally distributed. Lmer models were calculated for every outcome variable separately with initial PNR, SNR, operator's experience, operator's background, contraction level and type of simulated muscle set as fixed factors and simulated muscle (subject) as a random factor.

3 Results

The editing time was negatively correlated with the initial PNR value ($p < 0.0001$, F = 808; Figure 1A). The editing time also depended on the SNR value ($p = 0.0003$, F = 8.2; Figure 2A) as operators needed more time to edit MUs in signals with the SNR of 15 dB than 20 dB ($p = 0.0095$) and Inf dB ($p = 0.0003$). The operator's experience ($p < 0.0001$, F = 70.8; Figure 2B) and operator's background ($p < 0.0001$, F = 81.6; Figure 2C) were significant factors. Experts edited MUs more quickly than beginners ($p < 0.0001$) and semi-experienced operators ($p < 0.0001$). Operators with a background in physiology were faster at editing MUs than engineers ($p < 0.0001$). Contraction level ($p = 0.084$, F = 2.2) and muscle type ($p = 0.198$, F = 3.2) were not significant factors.

Similarly, the operators needed more actions to edit MUs with lower initial PNR ($p < 0.0001$, F = 780.3; Figure 1B) and lower SNR ($p < 0.0001$, F = 16; Figure 2D). Results show a significant increase in the number of all actions with MUs in signals with SNR of 15 dB compared to the 20 dB ($p < 0.0001$) and Inf dB ($p < 0.0001$). Experienced operators made fewer actions ($p < 0.0001$, F = 37.7; Figure 2E) compared to semi-experienced operators ($p < 0.0001$) and beginners ($p < 0.001$) The operator's background was also a significant factor ($p = 0.003$, F = 8.9; Figure 2F) as physiologists required fewer actions compared to the engineers ($p = 0.003$). Again, simulated contraction level ($p = 0.243$, F = 1.4) and muscle ($p = 0.214$, F = 3) did not influence the number of all used actions.

The number of add actions decreased with the initial PNR value ($p < 0.0001$, F = 605.2; Figure 1C) and SNR ($p = 0.033$, F = 3.4). Operators needed fewer add actions with signals that were generated with the SNR of 15 dB compared to 20 dB ($p = 0.024$). The number of used add actions decreased with the level of operator's experience ($p < 0.0001$, F = 25.2) as beginners needed to add discharges more time than semi-experienced operators ($p = 0.0164$) and experts ($p < 0.0001$). Also, semi-experienced operators needed more add actions than the experts ($p < 0.0001$). The background of the operators was not a significant factor ($p = 0.626$, F = 0.2) for add actions, nor was the contraction level ($p = 0.053$, F = 2.6) or muscle type ($p = 0.68$, F = 0.2).

The number of delete actions also depended on the initial PNR value ($p < 0.0001$, F = 687; Figure 1D) and SNR ($p < 0.0001$, F = 21.6). Operators used more delete actions with signals at SNR of 15 dB than 20 dB ($p < 0.0001$) and Inf dB ($p < 0.001$). The operator's experience did not influence the number of deletes ($p = 0.256$, F = 1.4). Physiologists again needed fewer delete actions ($p < 0.0001$, F = 33.8) than engineers ($p < 0.0001$). The operators needed fewer delete actions with SO than with BB ($p = 0.044$).
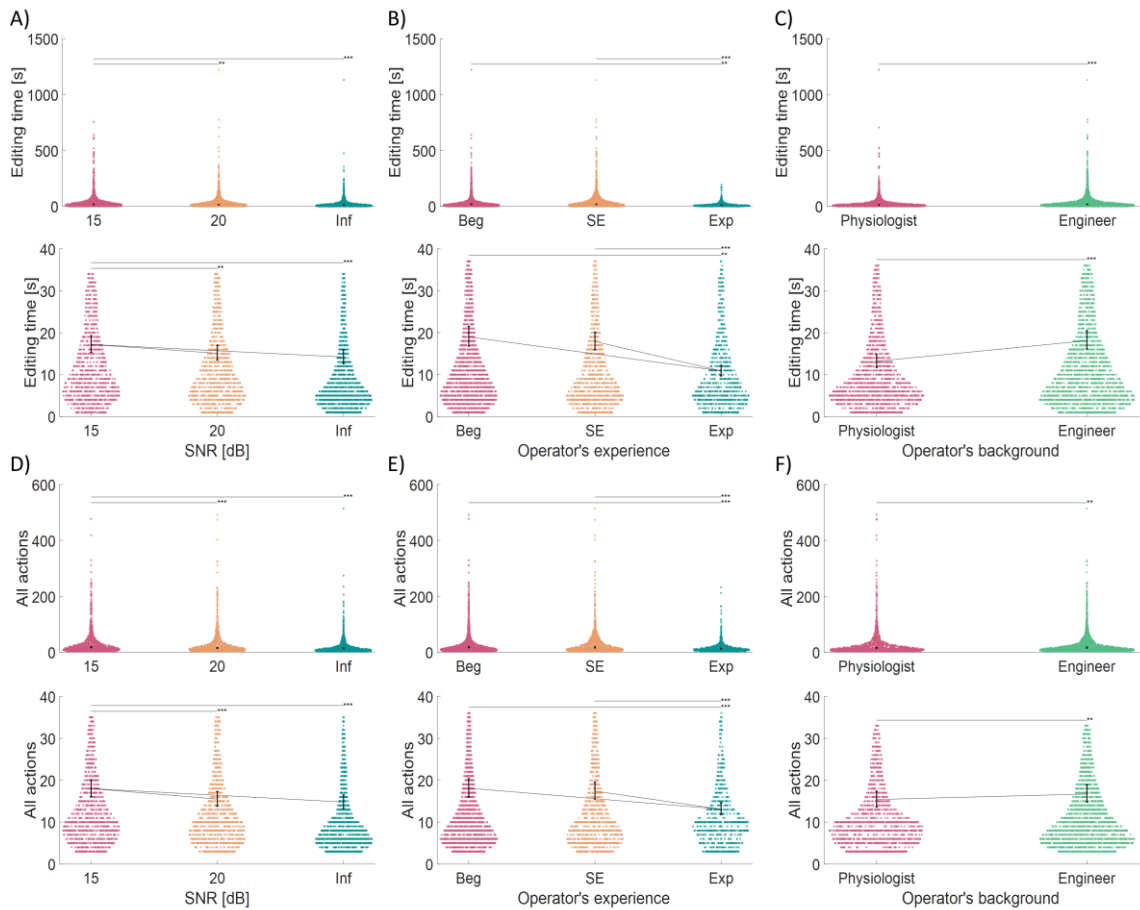
Figure 2: A) Editing time at different SNR values. B) Editing time of human operators with different levels of experience (Beg-Beginners, SE-Semi-experienced, Exp-Experts). C) Editing time of operators with different background. D) Number of all used actions within different SNR values. E) Number of all used actions across different operator's experiences. F) Number of all used actions across different operator's backgrounds.
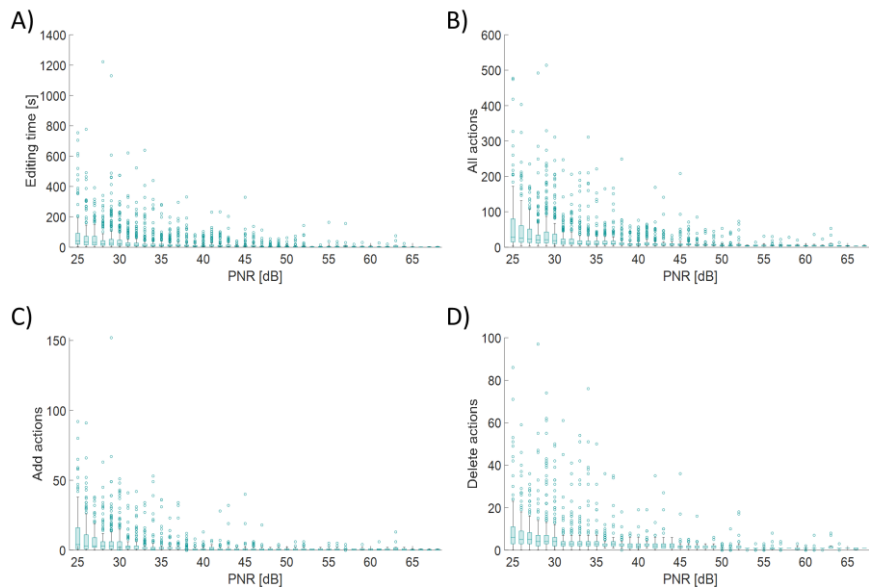

Figure 1: A) Editing time as a function of the initial PNR value. B) Number of all used actions as the function of the initial PNR value. C) Number of actions, used to add MU discharges as a function of the initial PNR value. D) Number of actions used to delete MU discharges as a function of the initial PNR value.

4 Discussion

The initial PNR value was a significant factor in all four outcome variables: editing time, number of all used actions, number of add actions and number of delete actions. The PNR value assesses the accuracy of the identified MU spike train and correlates positively with the sensitivity and precision and negatively with the false alarm rate [8]. MUs with lower initial PNR values were less accurately identified and needed more actions. The SNR was also an important factor in all the outcome variables.

Even though a higher contraction level causes an increase in the frequency of MU discharges and the number of recruited MUs, this study did not show a significant correlation with any of the outcome variables.

The operator's experience was a significant factor in most outcome variables: editing time, number of all used actions and number of add actions. However, it was not significant in the number of delete actions. These results suggest that with experience, operators gain a better understanding of MU behaviour, making editing steps faster.

Although manual editing may seem like a problem that mainly belongs to a signal processing field, there is still a need for physiological knowledge with which operators can understand and correctly classify discharges. With the more advanced knowledge of MU behaviour, manual editing becomes easier and demonstrates in shorter editing times and fewer actions needed by the operators with a physiological background.

Muscle was only significant with the number of delete actions, as operators needed fewer delete actions with the SO than the BB muscle. The latter is probably a consequence of MUs in SO having a higher initial PNR (40.1 ± 12 dB) than BB (33.4 ± 8.9 dB).

In conclusion, we performed an experiment where nine operators with different experience levels and different backgrounds manually edited the same dataset of decomposition results of synthetic signals. Results showed that the initial PNR and SNR correlate negatively with the editing time, number of all used actions, number of add actions and number of delete actions. Experience influenced the editing time, number of actions and number of add MU discharge actions. Results also showed that physiologists are faster and use fewer delete actions than engineers. Muscle was a significant factor in none of the outcome variables.

Acknowledgements

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