Supervised machine learning methods to identify muscles from MEP traces - a proof of concept design

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Introduction

It is challenging to look at a single graph of an unlabeled motor evoked potential (MEP) and identify the corresponding muscle. There is a high variability in MEP properties within and across patients even in the same muscle (Fig. 1).

Hence, we decided **to train standard machine learning (ML) algorithms and evaluate their performance** on this task.

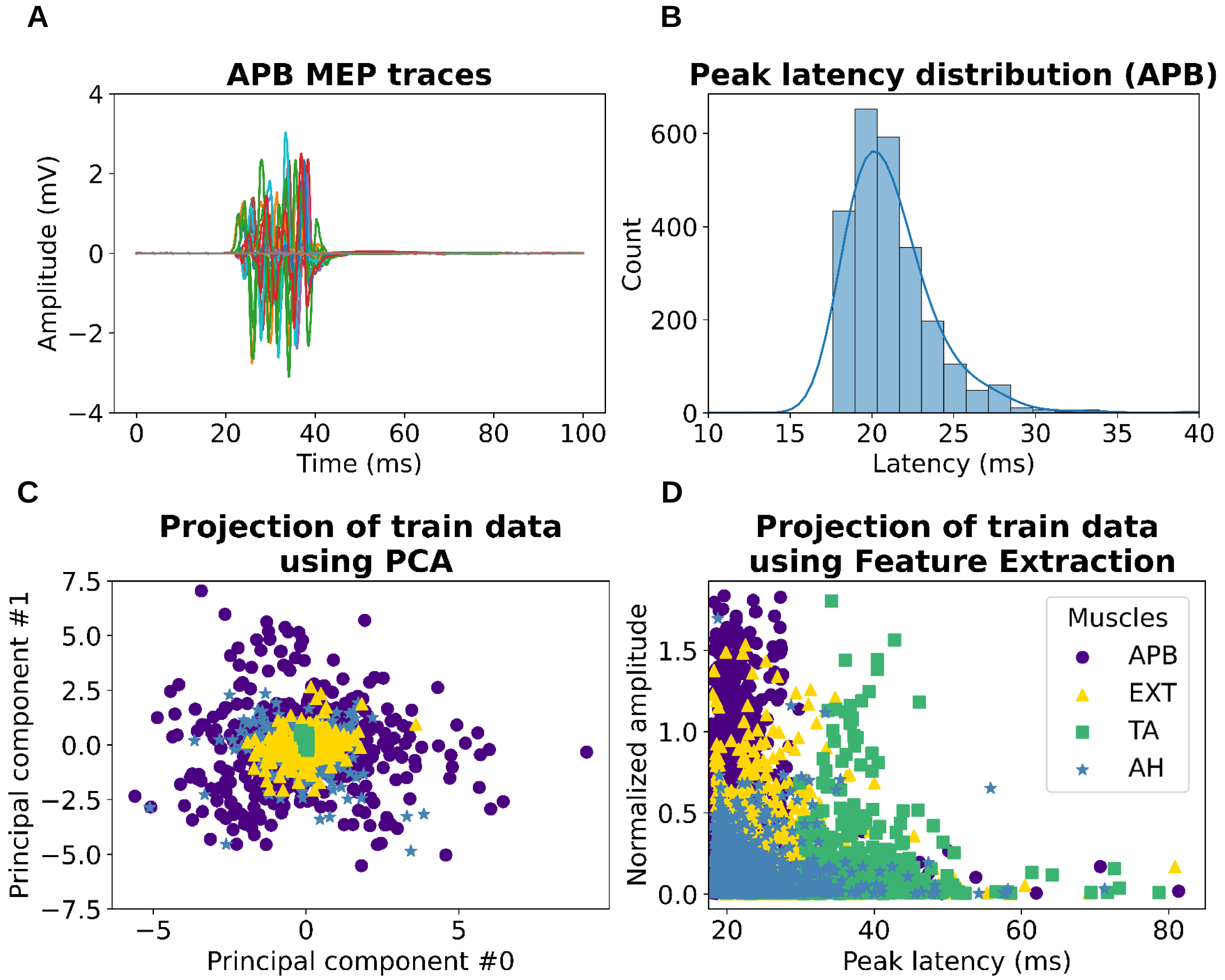

Fig. 1. Signal variability. (A) All APB MEPs from one patient. Even in cases where the signals are constrained, their morphology can be very different. (B) The peak latency distribution of all APB MEPs from all patients. (C) PCA plot of the two components which capture the most variability, showing that the MEP data is generally not well separable. (D) Projection of the training data on two important features. Again, this shows how much overlap there is across the different muscles

Methods

Intraoperative MEP data from surgery on 36 patients was included for the classification task with 4 muscles: Extensor digitorum (EXT), abductor pollicis brevis (APB), tibialis anterior (TA) and abductor hallucis (AH).

Three different supervised **ML classifiers (Random Forest (RF), k-Nearest Neighbors (kNN), and Logistic Regression (LogReg))** were trained and tested on **either raw or compressed data (with principal component analysis (PCA) and custom made feature extraction (FE)).**

Patient data was classified considering either all 4 muscles simultaneously, 2 muscles within the same extremity (EXT versus APB), or 2 muscles from different extremities (EXT versus TA).

In addition, we asked 30 expert neurophysiologists to fill out a questionnaire which showed labeled MEPs on the front and unlabeled MEPs on the back. The instruction was to "train" with the signals on the front and classify the MEPs on the back according to the 4 muscles.

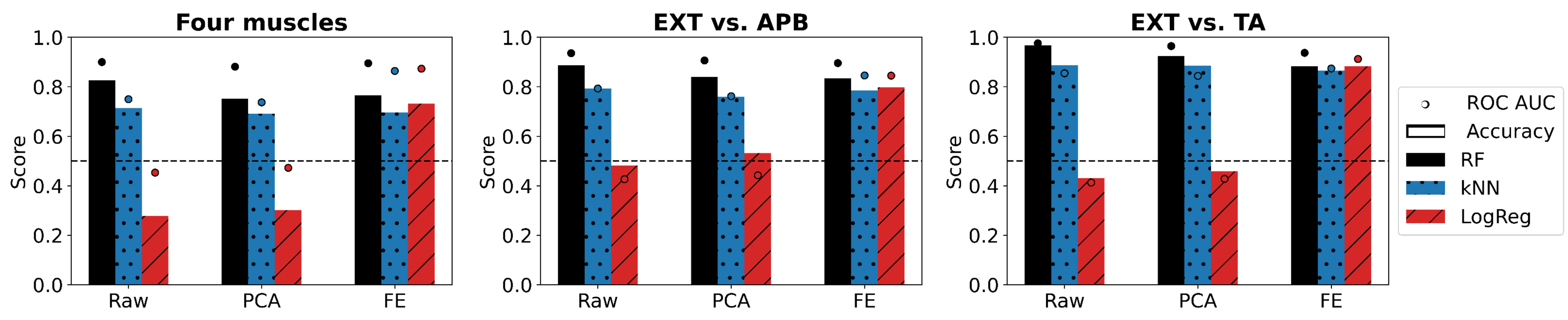

Fig. 2. Classification method performances. Depicted are accuracy (bars) and ROC AUC (dots) values for the color-coded algorithms. The RF classifier performed best overall and on the raw data in particular. The kNN classifier performed second best overall.

Results

A total of 3016 EXT, 3496 APB, 1451 TA and 835 AH MEPs were preselected and used for training and testing of the algorithms.

In all scenarios, **RF classifiers performed best and kNN second best** (Fig. 2). **The highest performances were achieved on raw data** (4 muscles 83%, EXT versus APB 87%, EXT versus TA 97% accuracy). For comparison, the mean accuracy on the 4 muscle classification task of the neuro-physiologists was 64% overall. The best model classified arm muscles accurately, but had more trouble with the leg muscles (Fig. 3).

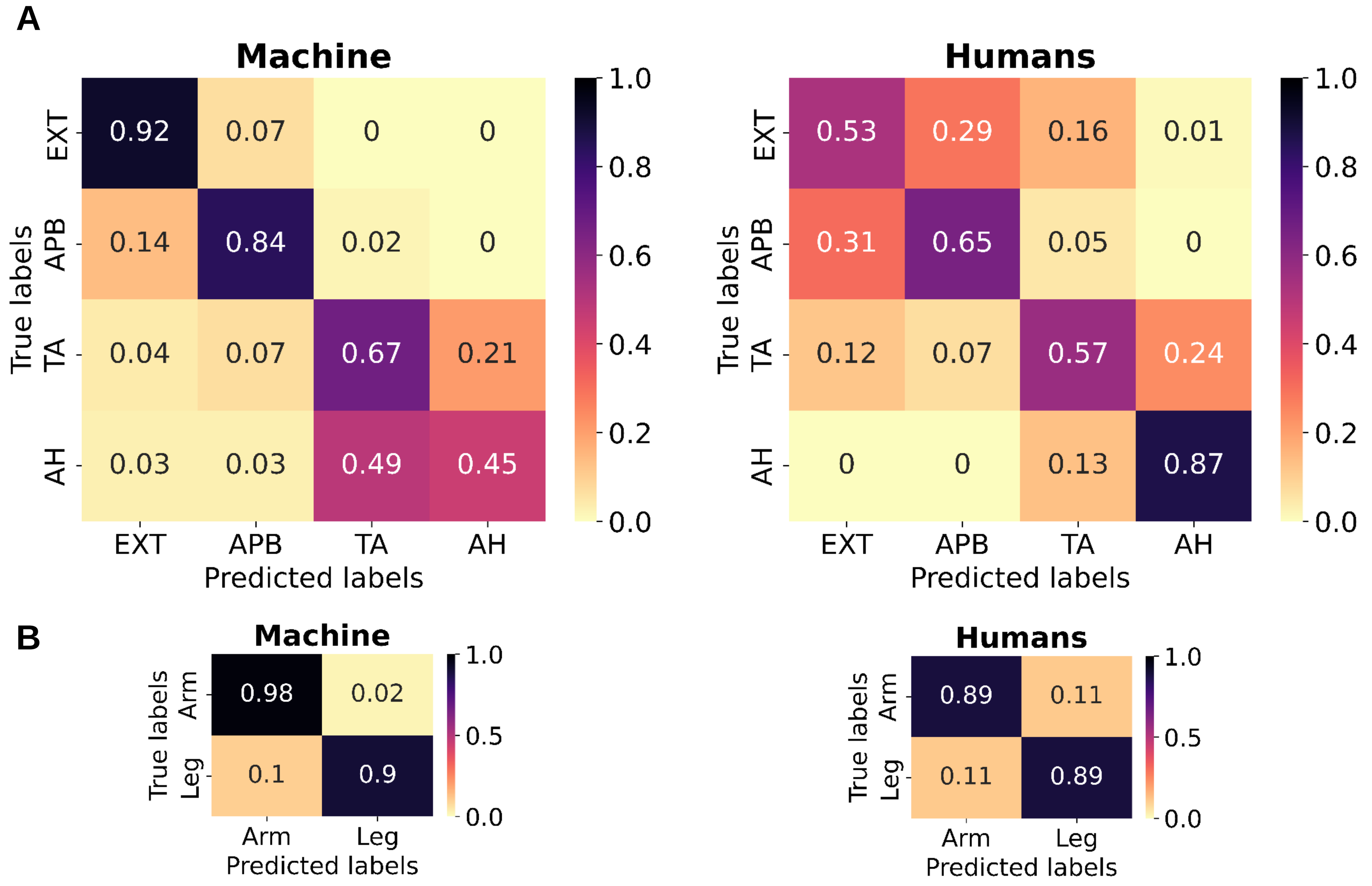

Fig. 3. Confusion matrix of best method (RF on raw data) and human classification. (A) Four-muscle performance. The algorithm classifies upper limb muscles very accurately, while its performance drops on lower limb muscles. By contrast, humans classify AH MEPs well because of their recognizable shape and amplitude. (B) Limb performance. Humans can easily distinguish upper from lower limb MEPs (due to the difference in latency).

Conclusions

- **Standard machine learning algorithms are able to classify motor evoked potentials according to muscle groups with high accuracy.**
- **Machine learning may help cope with the intrinsic difficulties of intraoperative neurophysiological data.**

Reference

Opportunities and challenges of supervised machine learning for the classification of motor evoked potentials according to muscles. *BMC Medical Informatics and Decision Making, (2023) 23:198*

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